



Advances in Mathematics for Industry 4.0



Edited by
Mangey Ram

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ACADEMIC PRESS

An imprint of Elsevier

Academic Press is an imprint of Elsevier
125 London Wall, London EC2Y 5AS, United Kingdom
525 B Street, Suite 1650, San Diego, CA 92101, United States
50 Hampshire Street, 5th Floor, Cambridge, MA 02139, United States
The Boulevard, Langford Lane, Kidlington, Oxford OX5 1GB, United Kingdom

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British Library Cataloguing-in-Publication Data

A catalogue record for this book is available from the British Library

Library of Congress Cataloging-in-Publication Data

A catalog record for this book is available from the Library of Congress

ISBN: 978-0-12-818906-1

For Information on all Academic Press publications
visit our website at <https://www.elsevier.com/books-and-journals>

Publisher: Mara Conner
Editorial Project Manager: Lindsay Lawrence
Production Project Manager: Bharatwaj Varatharajan
Cover Designer: Victoria Pearson

Typeset by MPS Limited, Chennai, India

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www.elsevier.com • www.bookaid.org		

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Preface

Mathematics is the strength of engineering sciences and Industry 4.0 is a name for the current trend of automation and data exchange in manufacturing technologies. It includes cyber-physical systems, the Internet of Things, cloud computing, and cognitive computing, that have important relationships.

Chapter 1, Trust enhancing technologies: blockchain mathematics in the context of Industry 4.0, analyzes the new framework with an especial interest on how “trust” and “privacy” are provided using blockchain technologies and considering also new regulations such as the European General Data Protection Regulation. Cybersecurity in Industry 4.0 is described by a new mathematical framework, involving innovative probabilistic and stochastic mechanisms and the graph theory, employed to describe complex relations and interactions between components in Industry 4.0 solutions.

Chapter 2, Optimization techniques to support decision-making processes via The MSM—an Industry 4.0 approach, presents the path to overcome two barriers. First, by proposing the link of MSM to an existing Internet-of-Things platform, taking advantage of the digitalization advent brought about by the Industry 4.0 revolution. Second, by proposing an optimization algorithm (integrated with discrete event simulation) that supports and facilitates decision-making based on MSM. Besides describing the proposed optimization approach, an application case study based on real industrial data from a company is presented and discussed.

Chapter 3, A probabilistic approach to reconfigurable interactive manufacturing and coil winding for Industry 4.0, describes how variability can be considered and mathematically described as part of the problem to obtain a flexible robotic solution.

Chapter 4, The tolerance scheduling problem for maximum lateness in Industry 4.0 systems, analyzes the scheduling processes in Industry 4.0 systems. A case of rescheduling on a single machine when the goal is minimizing maximal lateness is studied. Also, this is illustrated in the numerical analysis of a version of the study case, comparing the results with those of traditional rescheduling strategies.

Chapter 5, Digitization and security: a new challenge for Mathematics 4.0, provides a tool that transforms data into decision-making with the study of data—data science. The contribution of this chapter shows that data science consists of more components than just mathematics.

Chapter 6, Proposal and application of a framework to measure the degree of maturity in Quality 4.0: a multiple case study, proposes a framework to measure the Quality 4.0 maturity of companies that are adapting to the new paradigm of Industry 4.0. The framework covers the assessment of 11 organizational dimensions and the maturity degree is represented by five stages of evolution.

Chapter 7, Intelligent manufacturing as a social institute: internal and external regulation, discusses the process of institutionalization of intellectual production as an innovational approach to organizing the production processes in industry under the conditions of Industry 4.0. This chapter analyzes the modern global practice of regulation of industrial production: domestic regulation with the help of investment and innovational activity of industrial companies and external regulation with the help of stimulation of R&D, taxation, and development of infrastructural provision.

Chapter 8, Production planning and supply chain management under the conditions of Industry 4.0, focuses on the specifics of production planning and supply chain management under the conditions of Industry 4.0. and determines regional models of planning of production and supply chain management that exist in the modern global economy—the European and American model (applied by countries of West Europe and North America, for example, Germany, France, the United Kingdom, and the United States), the Asian model (applied by countries of Asia that specialize in industrial production, for example, Japan, South Korea, and China), and the Eurasian model (applied by countries of the CIS and the EAEU, e.g., Kazakhstan, Georgia, and Russia).

Chapter 9, Infrastructural provision and organization of production on the basis of the Internet of Things, determines the essence of the Fourth Industrial Revolution (transition to Industry 4.0) and its specific features, as compared to previous industrial revolutions. This chapter reveals the mechanism of overcoming the deficit and development of the infrastructural provision of production based on the Internet of Things.

Chapter 10, Artificial intelligence as the core of production of future: machine learning and intellectual decision supports, provides an algorithm of teaching artificial intelligence for the function of the provision of intellectual support for decision-making and for execution of the function of independent decision-making.

Chapter 11, Active digital manufacturing: conceptual foundations and practical solutions, develops the concept of active digital manufacturing, which predicts full-scale digital modernization of industrial production based on breakthrough digital technologies of Industry 4.0—cloud technologies, blockchain technologies, 3D printing, technologies of Big Data processing, the Internet of Things, artificial intelligence, robotronics, manipulators, and unmanned flying vehicles.

Chapter 12, Big Data management and data analysis: applied solutions in view of the spheres of the modern economy, is devoted to research into the process of application of breakthrough digital technologies, Big Data management, and data analysis for solving the current problems of statistical accounting and analysis given the spheres of the modern economy in the conditions of Industry 4.0. Also, an algorithm of statistical accounting and analysis of the spheres of the modern economy in the conditions of Industry 4.0 based on breakthrough digital technologies, Big Data management, and data analysis is offered.

In Chapter 13, Infusion-diffusion process-based modeling and profit estimation for manufacturing industries, a two-dimensional innovation diffusion model to formulate a framework, which optimally determines a firm's profit, taking into account the overall cost components associated with the initial experimentation cost and warranty outlay, is considered.

Chapter 14, Application of AHP in evaluating the financial performance of industries, deals with the application of the analytic hierarchy process to evaluate the mechanism for measuring industry's financial performance in India. This chapter presents four criteria: profitability indicators, solvency indicators, growth and efficiency indicators, and liquidity indicators. With this application, certain criteria will be ranked along with their subcriteria and, based on these, the key performance indicator is selected.

Chapter 15, Application of Internet of Things-aided simulation and digital twin technology in smart manufacturing, focuses on application of the IoT-aided simulation and digital twin technology in smart manufacturing in the context of Industry 4.0 and provides a reference model. The convergence of the digital world and the physical world, an important outcome of applying IoT-aided simulation and digital twin technology, enables smart decisions to be made at every point in the manufacturing operation, thus fostering a data-driven smart manufacturing environment.

Chapter 16, Mathematical models for dimensional accuracy of products generated by additive manufacturing, gives a review of the most relevant factors related to the dimensional accuracy and surface roughness of free-form manufacturing technologies, and the mathematical models that can help to guarantee adequate additive manufacturing process performance.

Through this book, entitled *Advances in Mathematics for Industry 4.0*, engineers and academicians can gain great knowledge and understanding of the mathematical applications in Industry 4.0. The material is intended for an audience at the level of postgraduate or senior undergraduate students.

Acknowledgments

The Editor acknowledges Elsevier for this opportunity and professional support. Also, he would like to thank all the chapter authors and reviewers for their contributions to this work.

Trust-enhancing technologies: Blockchain mathematics in the context of Industry 4.0

1

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Chapter Outline

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1.1 Introduction

Industry 4.0 (Bordel et al., 2019c) refers to a new technological revolution based on cyber-physical systems (CPS) (Bordel et al., 2017b). CPS are unions of physical and computational processes, which will be employed to create innovate and efficient control applications. These innovative solutions will be implemented in every system, solution, or infrastructure of future society. As a novel paradigm, CPS are described and managed by novel mathematical frameworks, typically based on control theory (where dynamical systems are extensively employed), instead of by traditional computational principles (supported by discrete mathematics and logic) (Bordel et al., 2018a). These new frameworks are being nowadays well investigated, as they are an essential first step before creating any Industry 4.0 solution. However, other transversal and related problems are not being studied in the same comprehensive manner.

In Industry 4.0 systems, processes and services will not be controlled by people through different technological solutions but managed by the machines themselves (Bordel et al., 2017a). In this context, trust in people operating systems is replaced by trust in mathematical algorithms describing the CPS' behavior (including decision-making algorithms, artificial intelligence mechanisms, etc.).

To enable trust on mathematical algorithms, CPS must be complemented with trust-enhancing technologies (Heurix et al., 2015). These technologies must guarantee, in a transparent manner, compliance with local regulation, data privacy, and data governance by owners among other requirements. In addition, all involved agents and stakeholders (workers, users, managers, etc.) need evidence that no agent can, individually, change the system behavior or break the rules (i.e., system governance must be decentralized) (Meng et al., 2018).

In this context, the traditional idea of “cybersecurity” is not enough to protect future Industry 4.0 systems against novel cyber-physical attacks, and mathematical frameworks and cyberprotection technologies, including the concepts of “trust” (Bordel et al., 2019b) and “privacy” (Kokolakis, 2017) previously described, are needed (Bordel et al., 2018b) (see Fig. 1.1). Nevertheless, as “trust” and “privacy” are nontechnological ideas, each particular trust-enhancing technology defines them in a different manner (Chen et al., 2015). Thus, before analyzing the new mathematics supporting the cyberprotection in future Industry 4.0, it is essential to select the technological mechanisms proving trust and privacy in these solutions.

Recently, Blockchain (Crosby et al., 2016) has arisen as the technology fulfilling this gap. Blockchain provides trust and privacy to a set of independent agents which do not trust each other by default but share information and collaborate. In order to do that, traditional mathematics related to data privacy and trust (e.g., encryption schemes, reputation algorithms, etc.) are replaced by totally different functions such as consensus algorithms, indirections, tokens, or hash trees (Pilkington, 2015). Moreover, Blockchain does not hide information to keep it secure, but establishes transparent controls to manage who accesses and manipulates that information. Therefore the use of Blockchain totally changes mathematical laws controlling cyberprotection, as stochastic dynamics and functions appear as main elements (Zyskind and Nathan, 2015). Graph theory (Deo, 2017), describing relations and interactions among components in Industry 4.0 solutions, is also employed.

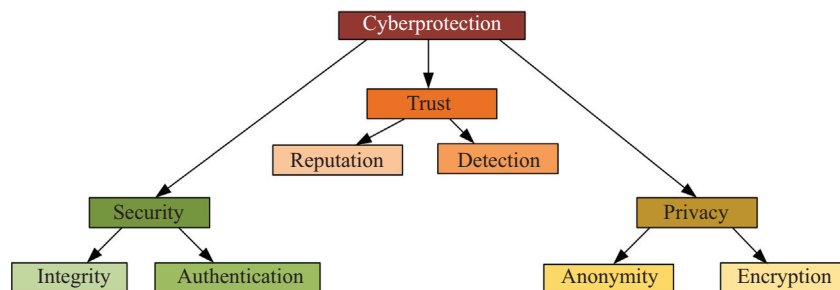


FIGURE 1.1

New concepts in the cyberprotection field.

In this chapter, we analyze the new mathematical models, algorithms, and laws controlling the behavior of systems in Industry 4.0, when protected using Blockchain technologies. Two basic aspects are addressed, in different subsections, including mathematical formalization and real examples:

- Trust for all (Yang et al., 2018): In this subsection, mechanisms employed to provide trust to all agents in Blockchain solutions are described. Random functions describing the Blockchain behavior are analyzed, including new vulnerabilities.
- Privacy by design (D’Acquisto et al., 2015): A decentralized data governance must guarantee data remain private (or are shared) according to laws designed by the owners. In this section securing functions that guarantee privacy are presented. In addition, indirections enabling information services (such as social networks) operate with data but without accessing the content are also described.

1.2 Trust for all

A Blockchain-supported mechanism $\mathcal{M}$ may be described as a tuple (1.1), including several elements. $\mathcal{D}$ is the information space, and nodes in the Blockchain network try to create consensus about data in this space. $\mathcal{B}$ represents the backbone of nodes enabling the operation of the Blockchain protocols and networks. And $\mathcal{C}$ represents the chain of blocks.

$$\mathcal{M} = (\mathcal{D}, \mathcal{B}, \mathcal{C}) \quad (1.1)$$

Considering the framework being described in this chapter, results and analyses are independent from the particular data being protected by the Blockchain mechanisms. Thus, although sometimes very specific models for the information space have been reported, in this chapter we do not consider any exhaustive description. However, some comments should be taken into account.

In all Blockchain-enabled systems, the protected data $\mathcal{D}$ are composed of some ($N_{\mathcal{D}}$) information units $\lceil_u$ that are indivisible. This can be, for example, account balances in the Ethereum network (Wood, 2014). Each information unit has a size of N_b , which determines the number of memory units (in bytes) required to store this information unit (1.2). Thus, to calculate the total memory MEM required to store the protected data we employ (1.3). This is essential as Industry 4.0 solutions are typically composed of resource constrained devices.

$$\mathcal{D} = \{\lceil_u^j \mid j = 1, \dots, N_{\mathcal{D}}\} \quad (1.2)$$

$$MEM = N_{\mathcal{D}} \cdot N_b \quad (1.3)$$

Focusing now on the underlying backbone, it is modeled by the connection graph $\mathcal{G}_{\mathcal{M}}$, oriented and weighted (1.4) (Bordel et al., 2019a). $VER_{\mathcal{G}}$ is the set of vertices of the graph, with $EDG_{\mathcal{G}}$ being the set of edges, and $\pi_{\mathcal{M}}^i$ the incidence

application of the oriented graph. Applying graph theory it is possible to define the connection graph as source $\pi_{\mathcal{M}}^s$ and target $\pi_{\mathcal{M}}^t$ functions:

$$\mathcal{G}_{\mathcal{M}} = (VER_{\mathcal{G}}, EDG_{\mathcal{G}}, \pi_{\mathcal{M}}^i) \quad (1.4)$$

Vertices and edges are related by source, target, and incidence functions, as described in (1.5). The source function associates each edge edg_i with the vertex ver_i , which is the origin of the edge edg_i . The target function associates each edge edg_i with the vertex ver_j , which is the destination of the edge edg_i . Finally, the incidence function relates each edge edg_i (outgoing from ver_i and incoming in ver_j) with the order pair of vertices ver_i, ver_j this edge connects.

$$\begin{aligned} \pi_{\mathcal{M}}^i & \text{UNDEFINED} & \text{ratio}; EDG_{\mathcal{G}} \rightarrow VER_{\mathcal{G}} \times VER_{\mathcal{G}} \\ \pi_{\mathcal{M}}^s & \text{UNDEFINED} & \text{ratio}; EDG_{\mathcal{G}} \rightarrow VER_{\mathcal{G}} \\ \pi_{\mathcal{M}}^t & \text{UNDEFINED} & \text{ratio}; EDG_{\mathcal{G}} \rightarrow VER_{\mathcal{G}} \end{aligned} \quad (1.5)$$

As the backbone must be represented through this model, it is important to provide a unique correspondence between Blockchain nodes and communication links; and vertices and edges in the graph. In particular, two bijections $(\{ver\}, \{edg\})$ are defined as the way to map the connection graph to the real network (1.6). Thus, for every pair of Blockchain nodes connected by a communication link, $\exists ver_i, ver_j \in VER_{\mathcal{G}}$ and $edg_i \in EDG_{\mathcal{G}}$ such that $\pi_{\mathcal{M}}^i(edg_i) = \{ver_i, ver_j\}$ and $\pi_{\mathcal{M}}^s(edg_i) = ver_i$ and $\pi_{\mathcal{M}}^t(edg_i) = ver_j$.

$$\begin{aligned} \{ver\} &: Blockchainnodes \rightarrow VER_{\mathcal{G}} \\ \{edg\} &: Communicationnlinks \rightarrow EDG_{\mathcal{G}} \end{aligned} \quad (1.6)$$

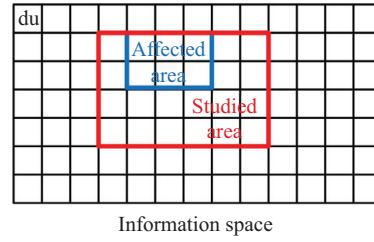
We also define the Blockchain as considering a duple (1.7) containing the initial (or genesis) information state C_{init} , and the ordered sequence of blocks $C_{seq} = (\lfloor_1, \lfloor_2, \dots)$. These blocks register all changes produced in the information space of the blockchain, stored as transactions. This sequence of blocks, in fact, depends on time $C_{seq} = C_{seq}[n]$, as it gets larger as time passes.

$$\mathcal{C} = (C_{init}, C_{seq}) \quad (1.7)$$

Information space contains trustworthy information if the chain of blocks described is valid, that is, blocks included in the chain and sequences are valid. We model a block $\lfloor_i$ as a packet containing three components:

- An unsorted list of transactions, which are information pieces describing changes in the information space since the last block was created;
- A reference to the previous block in the chain;
- Other data used for verification purposes.

Regarding changes in the information space, information units that are affected by transactions in a block belong to a subset named as “affected units,” $\mathcal{D}_{af-u}$. However, to apply changes in the affected units, a larger collection of units can be involved as references or dependencies. This new collection is called “studied units” $\mathcal{D}_{st-u}$ (see Fig. 1.2).

**FIGURE 1.2**

Information space in a Blockchain network.

There are some conditions and methods defined in Blockchain's specific consensus protocols to determine the validity of each block (and, then, of the entire chain). However, two generic conditions may be deduced as necessary to ensure the block validity:

- Coherence among transactions: All transactions must be coherent in relation to the information contained in the parent block and the studied units. For example, in the context of Bitcoin, no account can pay more money than it contains. Also, all money transfers must be deducted from the source account. To fulfill this condition, studied information units $\mathcal{D}_{st-u}$ and parent block information must be stored in nodes.
- Mandatory architectural requirements: Requirements such as consensus mechanisms [Proof of Stake (PoS), or Proof of Work (PoW)] must be fulfilled. These requirements are not dependent on the transitions or the studied information units.

Regarding consensus protocols, two processes (Baliga, 2017) are defined in the Blockchain and can be executed at any time. The fork choice process is a procedure employed to decide which sequence of changes in the information space (i.e., which chain of blocks) is the main chain. The main chain determines, finally, the official evolution of the information space and its current state. There is a probability that two or more blocks contain information describing contradictory changes in the information space. This situation is envisioned due to the probabilistic and distributed character of the block calculation process, and, to solve it, conflict-solving mechanisms are included in all consensus protocols to create information agreement among all nodes.

The actualization process is defined as the method employed by Blockchain participants to generate a new valid block and to chain it to the last valid block (this will be its parent block). At this point, it is necessary to specify some details about the architectural requirements for the valid block creation. Although different approaches have been proposed, such as PoS, currently, most extended Blockchain technologies require to pass a PoW. The PoW only admits a block as valid if its hash (according to a certain hash function *HASH*) concatenated with a

binary word named “nonce” is smaller than a certain value, H_{NON}^{MAX} (1.8). As the limit H_{NON}^{MAX} gets smaller, it is more difficult to find valid blocks; thus, H_{NON}^{MAX} is usually known as the “difficulty parameter.” This difficulty parameter may vary in time, although in most popular Blockchain implementations, the variation of this parameter is slow. For this theoretical analysis we are considering the ideal case of no variation of H_{NON}^{MAX} .

$$HASH([\]_i, nonce] \leq H_{NON}^{MAX} \quad (1.8)$$

As hash functions are pseudorandom functions (the output function is ideally unpredictable), the only strategy to validate (1.8) is to meet the architectural requirements, generating large quantities of *nonce* parameters. This process (known as mining) is, by default, an individual activity, that is, Blockchain nodes perform this process in an individual and isolated manner. However, in order to maximize the obtained rewards, sometimes nodes create pools or organizations to increase the valid block-finding rate. These organizations, in any case, are not officially recognized by Blockchain protocols, and consensus and agreement among agents in those pools must be reached by third-party procedures external to the Blockchain architectural conception.

The actualization process is successful when miners can satisfy (1.8). For a hash function with a p – bit output, and considering the difficulty parameter H_{NON}^{MAX} , then, the probability of a block to be valid, p_{valid} , is easily obtained considering the Laplace probability (1.9).

$$p_{valid} = \frac{H_{NON}^{MAX}}{2^p} \quad (1.9)$$

We are now defining a unitary miner, as a miner which can only perform a hash function evaluation per time instant, n_0 . Nonce candidates are equally probable, as hash function evaluations are independent events (Dworkin, 2015). In this context, a unitary miner may be modeled as a random variable, Y_{miner} , independent from time (as all hash evaluations are independent and unitary miners are, then, memoryless systems), following the Bernoulli distribution (1.10). Only two states are defined (success and nonsuccess) with probabilities p_{valid} and $p_{no-valid} = (1 - p_{valid})$.

$$Y_{miner} \sim Be(p_{valid}; success) = \begin{cases} p_{valid} success = 1 \\ p_{no-valid} = 1 - p_{valid} success = 0 \end{cases} \quad (1.10)$$

Considering a unitary computational power (1.11) for unitary miners, we model mining groups (nonunitary miners) as $Y_{non-miner}$, considering a superposition of pow_{comp} unitary miners, being pow_{comp} the computational power of the complex miner (1.12).

$$pow_{comp}(unitaryminer) = 1 \quad (1.11)$$

$$Y_{non-miner} = \{Y_{miner}^i, i = 1, \dots, pow_{comp}\} \quad (1.12)$$

These nonunitary miners, then, can perform pow_{comp} hash function evaluation at each time instant, n_0 . The probability for these nonunitary miners to generate a certain number v of valid blocks is, therefore, modeled by a binomial distribution (as it is a collection of independent Bernoulli trials) (1.13).

$$Y_{non-miner} \sim B(pow_{comp}, p_{valid}; v) = \binom{pow_{comp}}{v} p_{valid}^v (1 - p_{valid})^{pow_{comp} - v} \leq pow_{comp} \quad (1.13)$$

The Poisson distribution is the most employed model to describe Blockchain's behavior in terms of the block generation rate. Popular Blockchain implementations such as Bitcoin present long values of p_{valid} (hash output length in bits), but low values of the difficulty parameter H_{NON}^{MAX} (that is, high difficulty). In this case, the success probability p_{valid} tends to be very low. Moreover, miners provide high computational power, and pow_{comp} is a very high value. In those conditions, the binomial distribution converges to a Poisson distribution. However, in this chapter, we consider generic Blockchain systems, where this condition may not be met in general. In this general case, the binomial distribution cannot be replaced by a Poisson distribution, and this allows us to study special situations in modern Blockchain-supported systems.

On the other hand, the computational power of miners varies over time, because of the discretionary nature of the mining process and changes in hardware equipment. Then, nonunitary miners are finally modeled by a stochastic process (1.14).

$$Y_{non-miner}[n, v] \sim B(pow_{comp}[n], p_{valid}; v) = \binom{pow_{comp}[n]}{v} p_{valid}^v (1 - p_{valid})^{pow_{comp}[n] - v} \quad (1.14)$$

Now, we can model the block generation probability distribution in any pool of miners or Blockchain network, as the aggregation of all nonunitary miners in those networks (1.15). It must be considered that the number of miners could also change in time.

$$Y_{pool}[n, v] = \binom{pow_{comp}^{TO}[n]}{v} p_{valid}^v (1 - p_{valid})^{pow_{comp}^{TO}[n] - v} \quad (1.15)$$

$$being pow_{comp}^{TO}[n] = \sum_{\forall ver_i \in VER_G[n]} pow_{comp}^i[n]$$

Considering an attack aimed at compromising the information space stored in the chain, the risk can be calculated as the probability for an attacking pool of miners to create a chain of blocks with the potential to be declared as a main chain. Among the typical requirements that can be imposed on a chain to be considered as the main chain (chain containing the official changes in information space) the most accepted one is that the new chain must be as long as the current main chain (i.e., having, at least, as many blocks as the main chain).

We model the difference in length between the current official main chain, and the chain being calculated by the attacking mining pool as a Markov chain (Keilson, 2012). In this model, each state represents the difference in blocks

between the attacking chain's length and the current main chain's length, $U_{attack-chain} - U_{main-chain}$, in a given time instant. Null values in this Markov chain are calculated only for two states. State 0 describes two chains with the same length and the same blocks. State 0^* describes two chains with the same length but different blocks. When the alternative chain appears, the 0 state is not reachable anymore until the above-mentioned fork choice process ends. Apart from this consideration, all states in the Markov chain are connected.

The defined Markov chain is described by the transition matrix M_{tran} (1.16). Three different probabilities can be distinguished in this matrix: (1) the probability of remaining in the same state $\alpha_{same}(\bullet)$, (2) the probability of advancing toward states with a higher value $\alpha_{high}(\bullet, \bullet)$ (i.e., the relative difference between the original and the attacking chain grows up), and (3) the probability of advancing toward states with a lower value, $\alpha_{low}(\bullet, \bullet)$ (i.e., the relative difference between the original and the attacking chain decreases). In addition, parameters λ_1 and λ_2 may be as high as desired (in the limit case, even infinity).

$$M_{tran}[n] = \begin{bmatrix} \alpha_{same}(-\lambda_1) & \dots & \alpha_{high}(-\lambda_1, -1) & 0 & \alpha_{high}(-\lambda_1, 0^*) & \alpha_{high}(-\lambda_1, 1) & \dots & \alpha_{high}(-\lambda_1, \lambda_2) \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \alpha_{low}(-1, -\lambda_1) & \dots & \alpha_{same}(-1) & 0 & \alpha_{high}(-1, 0^*) & \alpha_{high}(-1, 1) & \dots & \alpha_{high}(-1, \lambda_2) \\ \alpha_{low}(0, -\lambda_1) & \dots & \alpha_{low}(0, -1) & \alpha_{same}(0) & \alpha_{same}(0) & \alpha_{high}(0, 1) & \dots & \alpha_{high}(0, \lambda_2) \\ \alpha_{low}(0^*, -\lambda_1) & \dots & \alpha_{low}(0^*, -1) & 0 & \alpha_{same}(0) & \alpha_{high}(0^*, 1) & \dots & \alpha_{high}(0^*, \lambda_2) \\ \alpha_{low}(1, -\lambda_1) & \dots & \alpha_{low}(1, -1) & 0 & \alpha_{low}(1, 0^*) & \alpha_{same}(1) & \dots & \alpha_{high}(1, \lambda_2) \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \alpha_{low}(\lambda_2, -\lambda_1) & \dots & \alpha_{low}(\lambda_2, -1) & 0 & \alpha_{low}(\lambda_2, 0^*) & \alpha_{low}(\lambda_2, 1) & \dots & \alpha_{same}(\lambda_2) \end{bmatrix} \quad (1.16)$$

These probabilities can be calculated periodically, considering the number of blocks that are being created and that are added to each one of the chains, as described in Eqs. (1.17–1.19). It can also be considered that block calculation in the attacking pool and the honest Blockchain network are independent events. It must be also seen that the explicit dependency with time has been removed for clarity, but all these probabilities depend on time.

$$\alpha_{same}(w) = \sum_{r=0}^{\min(pow_{comp}^{TO-main}[n], pow_{comp}^{TO-attack}[n])} Y_{pool}^{main}[n, r] \bullet Y_{pool}^{attack}[n, r] \forall w \quad (1.17)$$

$$\alpha_{low}(w_1, w_2) = \sum_{r=0}^{\min(pow_{comp}^{TO-main}[n], pow_{comp}^{TO-attack}[n]) - |w_1 - w_2|} Y_{pool}^{main}[n, r + |w_1 - w_2|] \bullet Y_{pool}^{attack}[n, r] \quad (1.18)$$

$$\forall (w_1, w_2)$$

$$\alpha_{high}(w_1, w_2) = \sum_{r=0}^{\min(pow_{comp}^{TO-main}[n], pow_{comp}^{TO-attack}[n]) - |w_1 - w_2|} Y_{pool}^{main}[n, r] \bullet Y_{pool}^{attack}[n, r + |w_1 - w_2|] \quad (1.19)$$

$$\forall (w_1, w_2)$$

At a certain time n_0 , the attacking chain is a relevant risk if the Markov chain is in any state with a positive value or in the 0^* state. Considering then an initial probability distribution $X^{n=0}$, describing the probability of the system to be at

each state at $n = 0$; the probability distribution of all states at time $n = n_0$ may be easily calculated through the transition matrix (1.20). Also, the probability for the alternative chain to be successfully recognized as the main chain is obtained by (1.21).

$$X^{n=n_0} = X^{n=0} \cdot \prod_{n=0}^{n_0-1} M_{tran}[n] \quad (1.20)$$

$$p_{valid}^{total} = \sum_m X^{n=n_0}(w) \quad (1.21)$$

$$\forall w > 0 \cup 0^*$$

There are two different strategies that can be adopted by attackers in order to validate their attacking chain. The first one is the “forward strategy.” In this strategy, attackers decide (in a certain moment) to build a secondary chain from the current point of the chain, that is, from the last discovered and valid block. This alternative chain may not be published soon, they can wait to publish the chain and, thus, perform the attack in the most adequate moment. The second one is the “backward strategy.” In this strategy, attackers select from which point on the chain they want to start the bifurcation, and then they plan the attack. From the mathematic point of view, the backward strategy is just a generalization of the particular case of the forward strategy, maintaining as a degree of freedom the decision of the block on which to carry out the attack. Then, as initial probability distribution, we are considering a distribution reflecting that the attack could start from any point in the chain of blocks with the same probability. Finally, we must consider that previous expression represents any attack started at any point in the chain of blocks, but always at $n = 0$. To consider attacks started at a generic time $n = n_{init}$ it is only necessary to apply a temporal displacement (1.22–1.23).

$$X^{n=n_0} = X^{n=n_{init}} \cdot \prod_{n=n_{init}}^{n_0-1} M_{tran}[n] \quad (1.22)$$

$$X^{n=n_{init}}(m) = \begin{cases} \frac{1}{cardC_{seq}[n_{init}] + 1} & w \leq 0 \wedge w \geq -cardC_{seq}[n_{init}] \\ 0 & w > 0 \cup \{0^*\} \wedge w < -cardC_{seq}[n_{init}] \end{cases} \quad (1.23)$$

Then, the probability of having a potentially valid main chain in an attack may be obtained by aggregating all possible cases (1.24).

$$p_{valid-chain}[n] = \frac{1}{n} \cdot \sum_{r=0}^{n-1} \left(\sum_{w} \left(X^{n=r} \cdot \prod_{h=r}^{n-1} M_{tran}[h] \right) (w) \right) \quad (1.24)$$

$$\forall w > 0 \cup 0^*$$

Attackers will wait to have a chain with the potential of becoming the main chain and then they will publish the attack. This attack forces a fork choice

process in all the nodes participating in the Blockchain. Nodes select one of the fork options (official and attacking chain) and then start mining on top of it. In practice, it is enough to get 51% of nodes in the network recognizing the new chain as the main change to get the attackers' objective (Cachin and Vukolić, 2017). In other words, in a general scenario where some nodes are miners and some are not, a block is accepted if, at least, 51% of miners which store any amount of information units belonging to the "studied units," $\mathcal{D}_{st-u}$, accept the new block, and mine on it, and the chain of blocks is accepted if the first (root) block is accepted.

1.3 Privacy by design

Research in data protection is very aligned to regulatory requirements compliance. There are many regulations followed by different countries. In this work we focus on one of the most current and extended among Europe, the "General Data Protection Regulation" (GDPR) created by the European Commission (Voigt and Von dem Bussche, 2017). In particular, GDPR identifies both, some required data protection features to all digital services, and up to eight users' rights to be preserved. Below, data protection requirements are briefly presented:

- REQ#1 Transparency: All Industry 4.0 services must process personal data in a transparent manner vis-à-vis data owners.
- REQ#2 Purpose limitation: Personal data can only be accessed and processed for legitimate and limited purposes, explicitly authorized by users and preferably with location and time constraints.
- REQ#3 Data minimization: Accessed and processed personal data must be just the required considering the purpose. Exposed data subsets must be personalized for each task.
- REQ#4 Accuracy: Industry 4.0 services must guarantee personal data are processed with accuracy and results updated if possible.
- REQ#5 Storage limitation: Personal data must not be stored for longer than required to reach the service objective.
- REQ#6 Integrity and confidentiality: Personal data must be always securely processed, transmitted, manipulated, and stored.
- REQ#7 Accountability: Mechanisms enabling users to check services compliance with the above requirements must be provided.

Apart from the requirements imposed by GDPR, current data protection solutions must be compliant with users' and consumers' rights (REQ#8):

- Right to provide unambiguous consent;
- Right that only relevant, necessary, accurate, and legitimate data are processed in a specific, fair, and transparent manner;
- Right to access one's own personal data;
- Right to be properly notified when personal data are used;

- Right to rectification;
- Right to protection against the use of personal data for automated profiling;
- Right to be forgotten;
- Right to security measures.

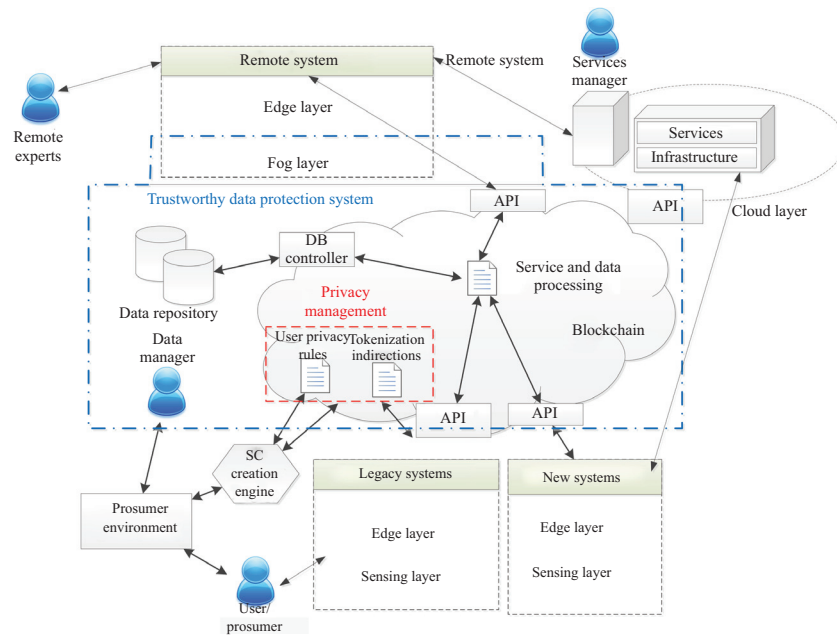
Some Industry 4.0 data protection algorithms and methods can satisfy the above-mentioned requirements by following a privacy-by-design (PbD) methodology (Cavoukian, 2009). In particular, a privacy-by-design approach improves privacy-enhancing technologies, for example Blockchain, enabling users the possibility to overcome the zero-sum argument by which either they share their personal data with Industry 4.0 services, or they cannot benefit from innovative services.

In addition to the previous requirement statements, any solution following the privacy-by-design approach must fulfill seven principles, described in this work as requirements:

- REQ#9 Proactive not Reactive; Preventative not Remedial: PbD methodology is focused on avoiding any privacy violation, even if no risk is perceived.
- REQ#10 Privacy as the Default Setting: All users are provided with the highest privacy level without action or request.
- REQ#11 Privacy Embedded into Design: Privacy is not an optional feature to add later in a system. Technological solutions must take care of privacy from the system's conception.
- REQ#12 Full Functionality—Positive-Sum, not Zero-Sum: PbD methodology must ensure that Industry 4.0 services can develop their business and users maintain their privacy at the same time; no dichotomy must arise.
- REQ#13 End-to-End Security—Full Lifecycle Protection: Personal data are private at all phases: from acquisition, to processing, storage, and destruction. The same privacy and security level must be guaranteed from start to finish.
- REQ#14 Visibility and Transparency—Keep it Open: Privacy-preserving instruments and mechanisms must be transparent and open, so users can check validity and performance of clear systems.
- REQ#15 Respect for User Privacy—Keep it User-Centric: In PbD methods, users' rights are the main element to be considered. Other components must comply with that to ensure users' data are always in the right hands.

Fig. 1.3 shows the proposed service architecture for future Industry 4.0 services, where data protection mechanisms are embedded into design (from the system's conception, not included as an extra functionality). Thus, REQ#11 is directly met.

The described architecture follows the edge computing scheme (Shi et al., 2016). Users (or prosumers, as they can also create their own privacy rules) are monitored through sensing elements which insert information coming from generic devices or through some industrial solutions that are installed in general-purpose processing components. As currently there are plenty of legacy systems for data acquisition in industry (Rosendahl et al., 2015), the proposed architecture

**FIGURE 1.3**

Proposed architecture for future Industry 4.0 services.

also provides a way to connect these legacy systems by data integration functionalities. All these devices make up a sensing layer which can operate in an autonomous manner.

These data are, then, stored in a trustworthy data repository (database) through a Blockchain network and an edge layer connected to the Blockchain using application programming interfaces (de Souza et al., 2004). This data repository belongs to users, and (by default) maintains data private and protected (nobody else has access permission). With this feature, REQ#10 is met.

In order to manage data from the data repository, a set of functions are defined in a database controller. This controller is embedded into a Blockchain network, so that off-chain security mechanisms can be improved with on-chain applications and services (authorization algorithms, privacy rules, etc.). In particular, all interactions with the database are public and irrevocable if accepted (for which a majority of service users participating in the network must approve the transaction). As transactions are public, and edge computing devices are operating with a Blockchain network, data must be encrypted, and devices authorized to operate with the Blockchain network. In any case, the use of these encryption schemes from the information generation moment guarantees REQ#6 and REQ#13 are fulfilled.

Moreover, a prosumer environment where users may create the privacy rules to be applied to their data is also considered. In this environment, users employ a domain-specific language to authorize Industry 4.0 services to operate with their personal data and create other privacy rules to be considered. Later, this description is translated into a deployable smart contract ([Christidis and Devetsikiotis, 2016](#)) in the SC creation engine. Data managers, in addition to prosumers, can implement other rules more related to regulatory requirements, for example, GDPR. Both SC, provided by prosumers and data managers, are related to data privacy, ensuring REQ#8 and REQ#15 are fulfilled. Moreover, SC in Blockchain are transparent pieces of code, public and with no access restrictions. In that way, privacy-preserving mechanisms turn transparent in our proposal, and REQ#7 and REQ#14 are met.

Industry 4.0 service providers must participate in the Blockchain network in order to work with the users' personal data. For this case they use an electronic identifier [in Blockchain, a public key calculated using Elliptic Curves ([Bauer et al., 2015](#))] that must be explicitly included in the privacy rules defined by users to grant permissions for the Industry 4.0 services (REQ#2). Then, using a new SC acting as linker, services (hosted in remote servers or in a cloud layer) request for the needed personal data to operate. This request is then redirected to the privacy management core, where an SC focused on tokenization and indirection accesses the personal data from the trustworthy repository. In this case, the raw personal data are not provided to the requester party. The tokenization/indirection SC returns to the service a token calculated with an indirection function, pointing to personal data stored in the trustworthy repository, which allows to operate with data but without sharing the real information. With these tokens, service providers may provide required services to their customers, but the results are not permanently accessible, as they can be modified when indirections are undone by users (data owners). This approach, based on edge computing schemes, prevents possible privacy violations, even if no risk is perceived (REQ#9). It also enables private information and service algorithms, supporting the business of Industry 4.0 service providers (REQ#12).

Parametric service results are only resolved in the edge layer, where devices belong to users. However, if remote experts (such as remote machine operators) must consume the service results, a new layer is necessary: the fog layer. In the fog layer a collection of nodes in the trustworthy data protection system resolves parametric results and indirections in a transparent manner vis-à-vis data owners (REQ#1). Thus, remote experts only obtain processed data and personal information according to the privacy rules defined by users, and only the essential information (not a complete copy of users' personal data). REQ#3 is, in that way, met. Processed results are, finally, sent from the fog layer to an edge layer where they can be manipulated, enriched, etc., by remote experts. Moreover, edge and fog layers will be configured to eliminate any parametric or resolved result after being consumed by users and/or remote experts. As devices in these layers belong to users, this requirement (REQ#5) may be easily met with guarantees.

Furthermore, it is possible for remote experts to also contribute generating more personal data or enriching it with more information. This new information will be incorporated to the trustworthy data repository following the previously described procedure. When new information related to a user is incorporated, this user and other authorized agents will be informed so that current services can benefit from this information. With this mechanism, REQ#4 is also fulfilled.

Considering this previous architecture, we are now analyzing the mathematical framework describing the behavior of these privacy-by-design mechanisms.

Participants in the trustworthy data protection system are provided with a key pair (asymmetric cryptography) for authentication purposes (named user operation key, key_{user}^{op}). As the user operation key can be stored in a remote host, additional security is required so that the private key information is not revealed. Therefore another key key_{user} (symmetric cryptography), known only by the owner, protects the previous key pair. The operation key is automatically calculated for every user through a digital signature scheme (DSS) (Nimbalkar and Desai, 2017). This DSS is defined as a 3-tuple (1.25), which contains a key generator Gen , a signature function Sig , and a verification procedure Ver . In our proposal, any existing DSS may be used, provided it is homomorphic.

$$(GenSig, Ver) \quad (1.25)$$

As is typical in Blockchain systems, information stored in the Blockchain is accessible by all participants. Our solution considers the application of encryption techniques to keep data secured. Using the proposed DSS, Industry 4.0 personal data can be encrypted by sensing elements. However, there are some problems that must be taken into account. First, sensing devices are defined as autonomous, therefore they must actuate without human intervention. Nevertheless, action from users must be requested in order to provide the secret key for the asymmetric mechanism in DSS, as this key, to be secure, cannot be embedded in devices or requested periodically. Second, remote experts, nodes in the fog or edge layers, and other agents different to the data owners could potentially be authorized to access to data. If data are encrypted, all these agents should be provided with the corresponding decryption key, which is totally unsecure. In addition, all permissions should be able to be revoked dynamically. Therefore the privacy management core and smart contracts in the trustworthy data protection system implemented a new and more complex cryptographic solution.

We define the operation user key, mathematically, as a key pair (1.26), containing a private user operation key $key_{user-priv}^{op}$ and a public user operation key $key_{user-pub}$. These two keys are obtained from the key generator Gen , using the user secret key and, optionally, an n-tuple of additional parameters $param_i$ increasing the generator entropy and then, the operation key quality (1.27).

$$key_{user}^{op} = \{key_{user-priv}^{op}, key_{user-pub}^{op}\} \quad (1.26)$$

$$Gen(key_{user}, \{param_1, \dots, param_n\}) = k_{user}^{op} = (key_{user-priv}^{op}, key_{user-pub}^{op}) \quad (1.27)$$

As DSS is homomorphic, such as in most popular DSS implementations (such ElGamal technique), homomorphic cryptography, encrypting Sig information $info_1, info_2, \dots, info_N$ obtained as compositions of various information pieces, is equivalent to encrypt each information piece individually, and apply a composition function that can be equal to $\otimes$ or different from $\odot$ the previous composition function (1.28). Although this requirement may seem difficult to fulfill, in fact many practical and common DSS present this characteristic (such as the ElGamal technique).

$$Sig(info_1 \otimes info_2 \otimes \dots \otimes info_N) = Sig(info_1) \odot Sig(info_2) \odot \dots \odot Sig(info_N) \quad (1.28)$$

being $\otimes, \odot$ algebraic operations

Then, to allow sensing and edge devices to interact with SC and the trustworthy data repository, a device key key_{device} for every component is secretly obtained by users. This device key is obtained through a second generator Gen_2 , which presents a similar structure to the previously described generator, Gen . In this case, the private operation user key $key_{user-priv}^{op}$ is used for decryption. An n-tuple of additional parameters $param2_i$ to increase the generator's entropy may be also considered (1.29). This new key generator, however, together with the corresponding device key pair, produced a piece of information $info_{device}$, which is unique for each key (and device), and that is named as the "homomorphic constant." As key generation functions are not invertible and device keys are obtained secretly, all security features are preserved. As already described, the device key is a key pair including a public device key $key_{device-pub}$ and a private device key $key_{device-priv}$.

$$Gen_2\left(key_{user-priv}^{op}, \{param2_1, \dots, param2_n\}\right) = \{key_{device}, info_{device}\} = \{(key_{device-priv}, key_{device-pub}), info_{device}\} \quad (1.29)$$

We also have to ensure that the private device key $key_{device-priv}$ presents an equivalence relation to the private user operation key $key_{user-priv}^{op}$ in the context of the signature function $Sig(\bullet)$, and supported by the homomorphic constant (1.30). In this expression, we define the $info_{device}$ as a homomorphic constant satisfying this relation between $key_{device-priv}$ and $key_{user-priv}^{op}$. As m_d is difficult to obtain, and private keys are already established and different in each side of relation (1.30), although the equation has a mathematical solution, the probability of a collision is very low, preserving resistance to the birthday attack. Moreover, currently existing hash calculation algorithms allow obtaining results fulfilling a set of preconditions in an easy and fast manner.

$$Sig_{key_{user-priv}^{op}}(info) = Sig_{key_{device-priv}}(info_{device} \otimes info) \quad (1.30)$$

being $\otimes$ algebraic operation.

Now, considering the previous expressions, and taking into account the selected DSS in homomorphic, the signature process of any personal information

$info$ may be written as an algebraic function involving a new constant $info_{device}^{signed}$ that is unique for each edge or sensing device (1.31)

$$\begin{aligned} Sig_{key_{user-priv}^{op}}(info) &= Sig_{key_{device-priv}}(info_{device} \otimes info) = \\ &= Sig_{key_{device-priv}}(info_{device}) \odot Sig_{key_{device-priv}}(info) = \\ &= info_{device}^{signed} \odot Sig_{key_{device-priv}}(info) \end{aligned} \quad (1.31)$$

being $\otimes, \odot$ algebraic operations.

Thus, in order to grant permissions to a sensing device so that it can interact with the data repository, the smart contracts, and in general, to the data protection system the corresponding SC (named as “service and data processing” in Fig. 1.3) must store just two parameters: the public user operation key $key_{user-pub}^{op}$, and the $info_{device}^{signed}$ parameter for each authorized device. As can be seen, both parameters are public and no personal information is involved or revealed. Also, authorized edge devices and other sensing devices contain the corresponding private device key $key_{device-priv}$.

The procedure to insert new personal information $info$ in the data repository is as follows: the sensing device must send to the SC (and together with the information) the corresponding signature $Sig_{key_{device-priv}}(info)$. In the SC, the signature is validated using only public information (already stored in the Blockchain), thanks to special properties of homomorphic cryptography (1.32). Only if $key_{device-priv}$ has been authorized and is valid will the signature be validated through the constant value $info_{device}^{signed}$. After the validation, the data repository is ready to accept the received information.

$$Ver_{key_{user-pub}^{op}}(Sig_{key_{user-priv}^{op}}(info)) = Ver_{key_{user-pub}^{op}}(info_{device}^{signed} \odot Sig_{key_{device-priv}}(info)) \quad (1.32)$$

Equivalently, the procedure to encrypt personal information m so that authorized devices can decrypt it, we use the public user operation key $key_{user-pub}^{op}$. The data description homomorphic cryptography (Patel et al., 2019) is again applied, identically to the previously described procedure. Authorized devices to decrypt personal information must include in the SC the corresponding homomorphic constant (different to the constant for the signature process), which is a public datum with no personal content.

This scheme is known to have many advantages. For instance, the smart contracts do not operate with any private key, as information managed by SCs can be public. The length of the key is also an important point, as the automatic generation of private keys allows us to select the appropriate key length in an unsupervised manner, thus maintaining the proposed security level. Finally, key substitution, due to possible leakages, bugs in software components, or cryptographic libraries, is possible and fast to apply, therefore cyber attacks based on statistical learning are very difficult to perform.

In order to provide temporal access for devices (edge and fog nodes) to private information we need dynamic authorization mechanisms, with the challenge of having external devices that can be hijacked, with the corresponding credential

leakage. Key distribution in this case is more complicated, and we opt for a token-based solution, as is described in the following scheme.

Users calculate a token *Token* for each remote agent using a specific token generator Gen_{token} . Parameters employed in this case for key generation are the public user operation key $key_{user-pub}^{op}$ and an n-tuple of additional parameters $param3_i$ to increase the generator entropy (1.33). The obtained token is sent to the remote agent seeking authorization.

$$Gen_{token}(key_{user-pub}^{op}, \{param3_1, \dots, param3_n\}) = Token \quad (1.33)$$

At the same time, the remote agent, using the previously described key generator (1.27), generates a new remote key key_{remote} (which is also composed by a key pair, including a private and a public key). In this case, however, only additional parameters $param4_i$ to increase the entropy during the generation process are injected in the generator (1.34).

$$Gen(\{param4_1, \dots, param4_n\}) = key_{remote} = (key_{remote-priv}, key_{remote-pub}) \quad (1.34)$$

Once the public and private remote key pair have been generated, the remote agent delivers the public one ($key_{remote-pub}$) to the data protection system, and this key will be saved in the SC. The publication of this public key does not produce any break in privacy. In order to request private data, remote nodes should send (along with the traditional data request) the received authorization token, signed with the private remote key $key_{remote-priv}$. When the signature is validated (as the public key is already available for validation), access is granted (1.35).

$$Ver_{key_{remote-pub}}(Sig_{key_{remote-priv}}(Token)) \quad (1.35)$$

The proposed mechanisms enable to revoke access permissions, invalidating access tokens, as well as securing essential private keys, which are stored only in trustworthy nodes. However, there is still an issue to be resolved in the model. Remote nodes and services, with the appropriate credentials, can obtain a copy of the user's personal data. As has been discussed previously, indirection techniques are defined in order to solve this. Using the proposed architecture (see Fig. 1.1) a remote Industry 4.0 service *Serv* is provided from the cloud. This service is represented as a function acting over a set of sequences of personal data $data_i[n]$ (1.36).

$$Serv(data_1[n], data_2[n], \dots, data_K[n]) \quad (1.36)$$

We define the *Serv* function as a composition of different functions (1.37): $Cloud(\bullet)$, $Fog(\bullet)$, $Edge(\bullet)$, and $Sensor(\bullet)$. These functions represent the service functionalities that will be executed in $Cloud(\bullet)$ the cloud, $Fog(\bullet)$ the fog layer, $Edge(\bullet)$ the edge layer, and $Sensor(\bullet)$ the sensing platform. The identify function

$Id(\cdot)$ will be employed when the service under study does not have any functionalities in a certain layer.

$$\begin{aligned} & Serv(data_1[n], data_2[n], \dots, data_K[n]) = \\ & = Sensor \circ Edge \circ Fog \circ Cloud(data_1[n], data_2[n], \dots, data_K[n]) = \\ & = Sensor(Edge(Fog(Cloud(data_1[n], data_2[n], \dots, data_K[n]))) \end{aligned} \quad (1.37)$$

On the other hand, a function for indirect access $Ind(\bullet)$ is defined in the SC in charge of tokenization. Each subset of information that is requested by consumer services is bonded to a token *Token* (1.38), which can be complemented with offset values Off_n for relative data addressing. Token calculation is, in our case, based on anticollision hash functions whose outputs are composed of a large number of bits (256 or even a higher number).

$$\{Token_i, Off_n\} = Inf(data_i[n]) \quad (1.38)$$

When service providers try to consume personal data, they obtain the above-mentioned token, representing those data. The token contains anonymous parameters representing real data, and operations performed by service providers over these data result in parametric services (1.39).

$$Cloud(\{Token_1, Off_n^1\}, \{Token_2, Off_n^2\}, \dots, \{Token_K, Off_n^K\}) \quad (1.39)$$

Parametric services are later received by the fog layer or the edge layer, depending on the case. Fog nodes are considered part of the trustworthy protection system, and, as edge devices belong to users, these two components may access clear personal data without compromising privacy in the system. No external agent gets a copy of the personal data being processed. In the fog and edge layers, tokens are resolved through an inverse indirection function, $Ind_{inv}(\bullet)$, also codified in smart contracts, and after exchanging data and resolutions requests (see Fig. 1.3) with the Blockchain network in the data protection system. Finally, these parametric services and resolution enabled by indirection functions allow the fog, edge, and sensing layers to eventually generate the final service result.

1.4 Conclusions, pending challenges, and future works

Industry 4.0 refers to a future industrial revolution, characterized by the use of Cyber-Physical Systems in every technological solution. In this context, new technologies to provide trust and privacy to future engineered systems are required. Blockchain solutions are, nowadays, the most promising mechanism to fulfill this gap.

In this chapter, the innovative mathematical models describing the behavior of Blockchain solutions are analyzed, considering the random variables that govern these mechanisms. In addition, graph theory is employed to represent the entire systems and the interactions among the different components that made up the

deployment. Indirection functions and encryption schemes are also combined to enhance privacy and trust provided by Blockchain solutions by default.

Apart from the proposed mathematical models, currently some relevant research lines and topic are being investigated. Some of the most important are described as follows:

- Traceability solutions (Bordel et al., 2018c), including those focused on controlling the movement of specific products (Alcarria et al., 2018) and those that are focused on guaranteeing the evolution and processing of large amounts of products (Bordel et al., 2019d). These solutions will be supported by Blockchain networks, either public solutions or private networks. Moreover, domain-specific or application-specific Blockchain implementations may be considered, as most current solutions, such as Ethereum, are open source.
- Modeling the information sharing in Blockchain-supported applications (Jang and Lee, 2017). Data flows in Blockchain networks have being modeled for most popular applications, such as Bitcoin, but works describing more general models have been also reported. These new models include both data formats and protocols controlling how information is shared between nodes, according to consensus and epidemic technologies.
- Defining new mathematical frameworks to prevent attacks to consensus protocols in Blockchain networks (Bordel et al., 2017c). Consensus protocols are well-known technologies, whose vulnerabilities have been studied for many years. However, how these weaknesses affect the entire Blockchain network is one of the most popular reach topics in this area nowadays. In particular, new attacks such as denial-of-chain or the 51% attack have been modeled and described, together with some initial solutions to prevent these vulnerabilities.
- Modifying the operation of protocols and mathematical algorithms in Blockchain to enable the integration of new types of data and information (Ahram et al., 2017). As described earlier, most Blockchain implementations are open source, so they can be modified to create application-specific solutions. New data formats, different from the typical accounts and smart contracts of Bitcoin and Ethereum networks, could be integrated in existing Blockchain systems to enable innovative solutions in a native manner.

Blockchain is envisioned to be employed in almost every future technological system. For this objective, some pending challenges must be addressed. Some of the most relevant pending challenges nowadays are also described below.

- Mathematical frameworks to describe the dynamic evolution of the underlying backbone in Blockchain-enabled solutions. Proposed models describe the behavior of nodes in the Blockchain networks, but this behavior is also affected by the variable configuration and architecture of the underlying backbone or communication network communicating with all nodes.

Integrating both effects will be very interesting in order to improve the precision of the defined models.

- New algorithms to implement additional security mechanisms such as digital watermarking (Shih, 2017). Exchanged data among the different nodes in Blockchain networks are nowadays encrypted in most secure applications, however additional protection mechanisms may be necessary to allow Blockchain-supported solutions to be implemented in critical infrastructures or similar scenarios.
- Integrating the characteristics of future 5G networks (Bordel et al., 2018d) in mathematical models for Blockchain solutions. Nowadays, Blockchain networks are designed considering some assumptions about traditional Internet and fixed networks. However, in future scenarios, nodes will be interconnected through mobile networks with a high performance. Analyzing and creating mathematical models to describe Blockchain solutions supported by future communication technologies such as 5G networks is one of the most relevant and promising pending challenges.
- Defining complex models for final applications in Industry 4.0, such as SmartGrids or Smart Homes (Alcarria et al., 2017). Blockchain as an enabling technology to create innovative solutions to share and distribute sparse resources in a trustworthy manner must be investigated. In these scenarios, more general solutions are implemented, whose high-level behavior is pending to be modeled, although it is based on Blockchain protocols.
- Mathematical models describing the aging procedure of hardware, so the probability of finding a block may be particularized for each time instant and hardware architecture. In that way, the proposed models for the evolution of information and blocks in future Industry 4.0 systems will improve their precision.

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Optimization techniques to support decision-making processes via MSM—an Industry 4.0 approach

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2.1 Introduction

To reach highly competitive levels, companies need to adapt their production tactics to equal or even exceed the market competition. In this context, current industries are engaged in simultaneously reducing different waste sources and increasing overall productivity, therefore enhancing the value of their products and achieving operational excellence ([Dametew et al., 2016](#)).

With all this in mind, industries must trace objectives that fulfill their economic goals in a sustainable manner. One of the most quoted definitions of sustainable manufacturing is given by the US Department of Commerce, which states “sustainable manufacturing is the creation of manufactured products that use processes that minimize negative environmental impacts, conserve energy and natural resources, are safe for employees, communities, and consumers and are economically sound” ([International Trade Administration \(ITA\), 2010](#)).

Those realistic trade-offs between business and performance concerns are highlighted by an ongoing European project named MAESTRI that, as Schneider et al. (2015) states, “aims to encourage a culture of improvement within manufacturing and process industries by assisting the decision-making process, supporting the development of improvement strategies and helping to define the priorities to improve the company’s environmental and economic performance.”

While evaluating these parameters might appear simple, using them for decision-making can be more difficult, as these objectives must meet requirements regarding the impacts on employees, community, and especially on the economic aspects ([Kulatunga et al., 2015](#)).

One powerful tool to support companies overcoming this challenge is the Multilayer stream mapping (MSM) method. This has the ability to identify critical performance processes and activities, allowing the signalization to consider the implementation of continuous improvement actions. As discussed in Section 2.2, as many streams as possible should be used to diagnose the production system, however this creates the need for massive data gathering and makes it more difficult to identify where and how to change or improve first. Therefore in the next section an explanation of MSM is given, as well as the benefits of its integration with automatic data gathering by implementation of sensors in equipment and operations sensing, and the use of the Internet-of-Things (IoT) platform. In Section 2.3, a methodology is proposed to apply optimization techniques aiming at supporting decision-making on what actions to take to improve the performance indicators (assessed by MSM). In Sections 2.4–2.7, the methodology is deployed by an application to a real case to demonstrate the potential of the proposed methodology. Therefore the purpose of this chapter is to describe and apply a possible path to use MSM under the Industry 4.0 concept and to facilitate its application and use in the decision-making process with the use of an optimization algorithm integrated with discrete event simulation. This is an important new step and scientific/industrial contribution in the application of the MSM approach,

in the form of a software tool, leveraged by the application of different tools from the Industry 4.0 scope.

2.2 The multilayer stream mapping approach

The MSM method was originally developed, between 2012 and 2013, at INEGI—Portugal, to create an approach, based on lean principles and value-stream vision, for time and resources consumption efficiency assessment of production systems (Baptista et al., 2016). While evaluating the productivity and efficiency of resource utilization, waste and other process domain variables are analyzed in an integrated from.

The increasing need for greater competitiveness and productivity, high costs of resources, and the demands of a changing worldwide market create enormous challenges to production management (Lourenço et al., 2016). Therefore resorting to the necessity of improving overall efficiency of production systems, by reducing waste components, MSM arose and was announced as a powerful tool to evaluate the time and resources consumption efficiency, and its relation to waste, through detailed phases as expressed in Fig. 2.1.

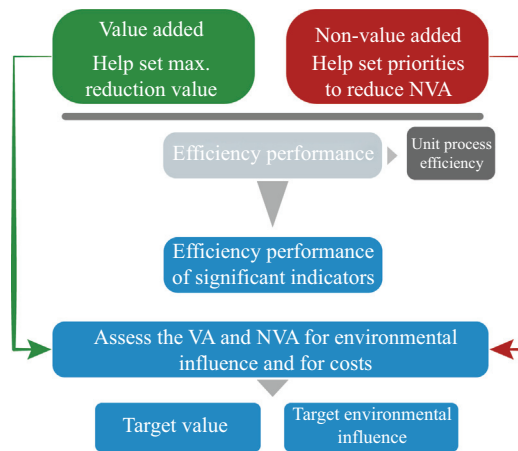
The MSM focus on the diagnosis of each product permits a straightforward interpretation and direct understanding of those results to quickly identify critical aspects and inefficiencies of the system, due to its intuitive visual layout (Lourenço et al., 2016; Gomes, 2016).

Thus, the lean manufacturing value stream mapping roots are transformed into the MSM concept to diagnose and analyze the overall efficiency of a production system, but also taking into account the environmental and economic performances, while simplifying the quantification of waste activities (Baptista et al., 2014; Covas, 2017).

Nonetheless, this lean-based tool is intended to be used, not only for analytical evaluation, but also to support the decision-making process. Enabled by the IoT platform in a company the decision-taker can evaluate decisions, related to:

- Identification of the most critical resource or process parameters;
- Recognition and quantification of the inefficiencies of a given production system and unit process;
- Assessment of both resource and operational efficiency (including flow efficiency) and overall production system performance;
- Disaggregation of costs for each process step and process variable/indicator; accounting for the value-added and nonvalue-added components;
- Foster implementation of improvement and optimization actions;
- Evaluation of efficiency progress, promoting continuously improved sustainability within organizations.

Therefore MSM is mainly an assessment tool. Thereupon, an expert must analyze them and support improvement suggestions on presented metrics.

**FIGURE 2.1**

Schematic representation of the MSM methodology.

Adapted from Baptista, A.I. et al., 2015. Technology watch report. Maestri Technology Report.

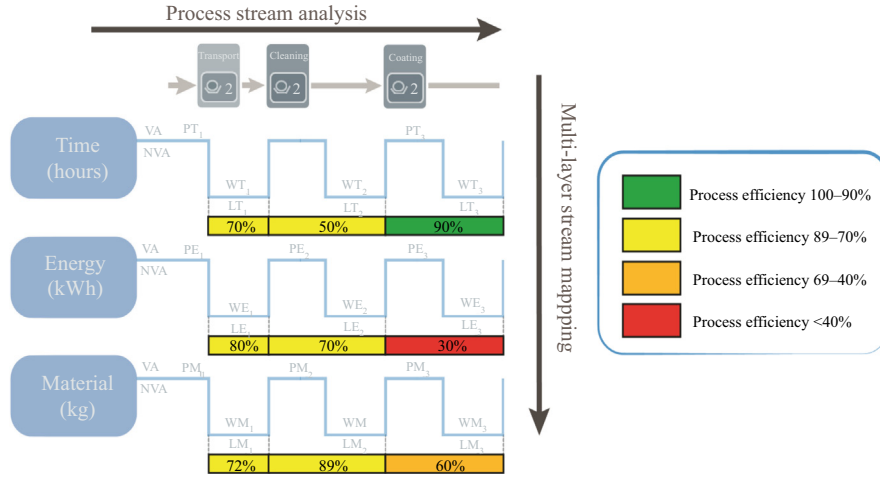
The MSM method outlines efficiency performances and lays them out in a simple manner through a visual platform (“MSM scorecards”) to simplify the understanding of performance indicators, as well as their suitability for decision-making. This leads to a visual management of the presented metrics supporting a sustained decision process.

The MSM methodology resembles a matrix, such as that depicted in Fig. 2.2, where rows are associated with the different variables/indicators/KPI chosen to evaluate the system, and columns illustrate the different steps of the production system, designated by processing units. The MSM scorecards can in some application scenarios be changed in the “columns definition,” namely when assessing a given machine (process step) where the scorecard columns can retrieve the time scale disaggregation and evolution on each KPI (e.g., Days, Weeks, Months, etc.).

Due to its visual and alarmist outlook, a set of colors is used to ease the interpretation of results and spot critical inefficiency situations. This method makes it quicker to assess the efficiency result while contributing to prioritization of improvement actions and enhancing continuous improvement (Covas, 2017).

As it intends to be a lean tool to diagnose and monitor production systems, “value” and “waste” concepts are always implicit. In MSM each variable being analyzed has a line following through different processes that constitute the value stream. The values located below this line are those which represent the nonvalue added (NVA) to the product. The values above the line indicate the value added (VA) to the product, representing useful consumption (Covas, 2017).

An updated and important evolution to the MSM methodology was proposed in 2016 by IST researchers collaborating with INEGI (Gomes, 2016), by the assertions that NVA phases like setup, transports, storages, and waiting times are

**FIGURE 2.2**

Schematic representation of the MSM methodology.

Adapted from Baptista, A.I. et al., 2015. Technology watch report. Maestri Technology Report.

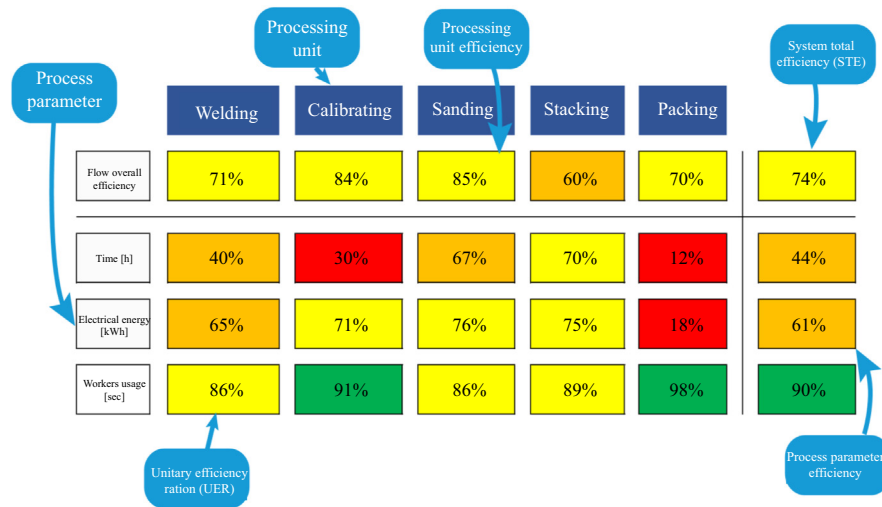
essential activities to study since they consume resources like time, energy, or materials, and consequently have costs to the company and influence on the system performance. Therefore this new potentiality integrates the waste activities in the original methodology, making it possible to obtain entire product flows (Gomes, 2016; Covas, 2017).

The MSM methodology promotes an extensive comprehension of the current system performance, regarding flow and resources. Each process has an associated performance unitary efficiency ratio (φ), which in its base form can be calculated by means of Eq. (2.1):

$$\varphi = \frac{VA_{fraction}}{VA_{fraction} + NVA_{fraction}} \quad (2.1)$$

All this information can be displayed in dashboards such as the one presented in Fig. 2.3. From top to bottom, all teams must understand the scorecard without losing too much time identifying critical process parameters for rapid improvement (Gomes, 2016). This immediacy is only achievable with constant and holistic data tracking of the production system objects.

To accomplish the above, the data acquisition and processing should be considered throughout, for instance by means of an IoT platform. The use of sensors installed in equipment and material flow points, connected through the IoT to data processing and visualization screens, enables the almost real-time performance of several production systems components. Therefore MSM is a tool to support the link between the physical and digital worlds, having high potential to be used in cyberphysical production systems.

**FIGURE 2.3**

Efficiency calculations through MSM.

Adapted from Baptista, A.I. et al., 2015. Technology watch report. Maestri Technology Report.

Solving the mentioned first barrier of MSM, the user is faced with the difficulty of decision-making due to the dozens of performance ratios per MSM screen or board. The possibility of a high number of streams makes it difficult to identify what actions to take regarding continuous improvement projects. There is always the possibility of reducing the number of visible streams, but then problems of lack of information might occur. Besides the difficulties and critical aspects of using MSM scorecards for a large number of process steps (machines, equipment systems, etc.), it is fundamental for the digitalization of the production system to assess, a gap which can be fulfilled by part of the Industry 4.0 paradigm implementation. Nonetheless, another gap in the MSM approach is in regard to the fact that, after a given assessment is made, who should determine the overall improvement scenario that reduces the waste and, consequently, improves the system total efficiency. For that, the solution can be based on the following sections, where simulation and optimization techniques are proposed to assist humans in the decision-making process, based on MSM indicators.

2.3 A synopsis of the proposed methodology

The main objective of the proposed methodology is to help the production decision-maker to decide what production and planning parameters to change to improve the system performance (measured by the MSM indicators). Through

simulation and optimization algorithms the parameter setting that maximizes the indicators can be found, supporting more informed decision-making. The parameters changing will impact the NVA activities, and therefore change the flow and resources efficiencies of the production system. It is expected that this approach will help the decision-making process and the creation of new strategies.

This approach comes under the scope of operations research (OR). Therefore optimizing an industrial process via the MSM tool is clearly talking about applying OR to problems that concern how to conduct and coordinate the operations within an organization (Hillier and Lieberman, 2001). The goal of OR is to provide rational bases for decision-making by seeking to understand and structure complex situations, predicting the system's behavior, and improving system performance (Heger, 2006). Therefore the six phases of this technique are enumerated based on Hillier and Lieberman (2001):

1. Define the problem of interest and gather relevant data;
2. Formulate a model to represent the problem and validate it;
3. Develop a computer-based procedure for deriving solutions to the problem from the model;
4. Test the model and refine it as needed;
5. Prepare for the ongoing application of the model as prescribed by management;
6. Implement.

Apart from its common application, the great novelty of this study consists in analyzing the usage of MSM to simulate scenarios right before its implementation on the shop-floor. It allows top teams to choose the best working plan according to the goal that is being attempted to be achieved. Accordingly, Fig. 2.4 depicts the problem and a brief explanation is given forthwith.

First, coupling the production system characterization with real data gathering allows for the definition of the problem and accounts for inferring useful and meaningful indicators to diagnose the system via MSM.

Resorting to the second phase of an OR procedure, a model emerges as the real production system translation. This model will be the stage of crucial simulations after its validation. It considers a requested production plan to simulate different imposed scenarios.

Then, the company top teams define an objective or cost function that fits the strategy that they wish to follow. With an optimization technique, the production system's performance is improved, and a suboptimal solution arises. The optimization procedure uses the model developed to run simulations and then calculates MSM metrics that are part of the cost function.

Finally, it is supposed to support a decision-based process that aims to improve production efficiency. It will allow the simulation of scenarios in which different strategies are tested and only the best one, based on the defined MSM metrics, is implemented in the shop-floor. Then, in addition to using MSM as a

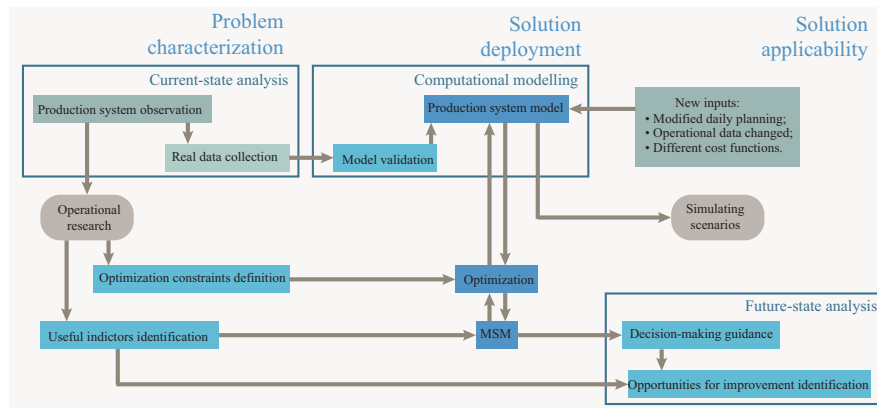


FIGURE 2.4
Methodology outline.

way of reducing inefficiencies after production, an a priori analysis can be helpful to increase the company's efficiency.

2.4 Problem statement—a real case study

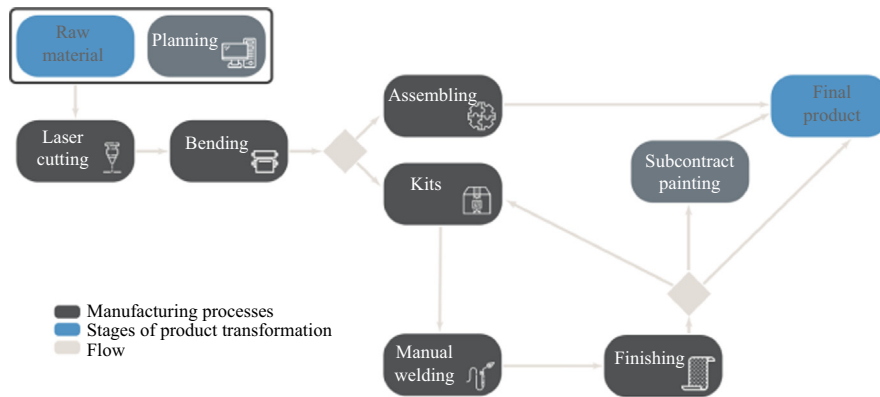
2.4.1 The company and the production system

Company A is a metal component and assembly manufacturer that already counts on around 60 years of experience. All data were gathered by visual observation, time measurements and interviews with operators, making sure that the usual work and the employees' jobs were not destabilized. This contributed to the production system model creation and its consequent validation, to ensure that it represents the real system behavior as far as possible.

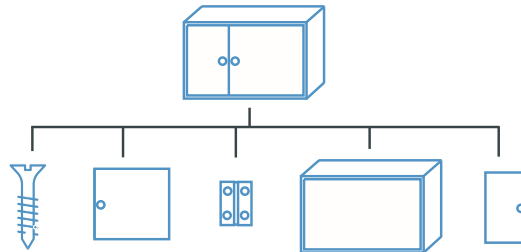
The productive units involved in this study have several components such as production machines, material handling systems, computer software to coordinate tasks, and human workers to operate and manage the system.

The company market position is associated with floating demands and customized orders that define what, when, and how much it is necessary to produce, meaning that company A rules its planning based mainly on *pull production*. Therefore the current system uses a *make to order* manufacture logic that is based on the quotidian demand.

Regarding the shop-floor layout classification, this type of manufacturing process is designated by *job shop production*, which is based on the process outline itself. In other words, similar operations are aggregated in unit processes, and products go through a specific sequence within each unit process, as described in Fig. 2.5.

**FIGURE 2.5**

Processing units' precedence constraints schema.

**FIGURE 2.6**

BOM example.

The company A production approach assumes that a job may be processed on a particular machine at most once during its route through the system (Pinedo, 2005). Indeed, the exhaustive planning for sequencing the requirements of each product, capacities for each work center, and order priorities are mandatory in a job shop (Kumar and Suresh, 2008).

In company A, not only is managing resources a hard task, paying attention to the bill of materials (BOM) of each end product is also required (see Fig. 2.6). In fact, subassembly operations are performed in different unit processes, such as in the manual welding or kits sections. In this way, it can be considered an *assembly job shop* scenario.

2.4.2 Processing characteristics and job constraints

Also, this company has at its disposal both manually operated machines (controlled or supervised by a human worker) and semiautomated machines (that

perform a portion of the work cycle under program control and the remaining work under the handling of a worker).

The product flow in company A is subjected to particular constraints based on the job-shop characteristics, with the most relevant ones to this case study listed below (Pinedo, 2005):

- *Precedence constraints*: In scheduling problems, a job often can only start after a given set of other jobs has been completed (Fig. 2.5);
- *Machine eligibility constraints*: Some jobs can be assigned only to specific machines;
- *Workforce constraints*: Some tasks and machines require more than one operator;
- *Sequence-dependent setup times and costs*: Machines often have to be prepared for the next job (setup or cleaning between jobs);
- *Storage space and waiting time constraints*: The limited space available for work in progress (WIP) storage puts an upper bound on the number of jobs waiting for a machine. A full buffer prevents a machine from processing the next job.

In addition, there is the precedence constraint. A higher level item cannot be processed unless all preceding lower level items are assembled. All the precedence constraints must be respected in physical production, and naturally its consideration is of the utmost importance in constructing the production virtual model.

2.4.3 Manufacturing processes description

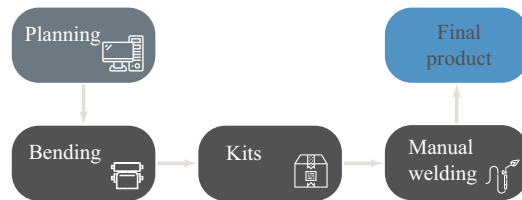
For the sake of controlling the complexity of the proposed approach application, only the order planning, and bending and welding processes were considered, together with the kits zone (a WIP area), the connecting block between those two main processes, as illustrated in Fig. 2.7.

Orders planning. The daily work is defined a priori based on an Excel list of budgets and projects already approved.

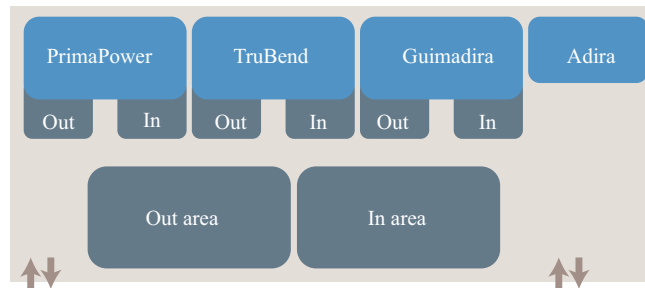
This delineates exactly which processes the manufacturing order (OF) must pass through as well as the times of each operation to be performed. Hence, it also creates a correspondence between the BOM and each one of those OFs.

Bending. This workstation configures, by the action of a pressure force impelled by a machine, the required parts into its final desired shape.

This section has four different machines, a semiautomatic one that limits depth-level operations, two manual machines, and a conventional one. The first three machines are capable of counting pieces, which makes the worker's procedure easier and faster. Each one of these appliances has its own characteristics, such as power supply and cost by working hours. The bending section layout is represented in Fig. 2.8. There, it is possible to distinguish two main distinct areas and, within these ones, further smaller ones, that feed each machine, the IN and OUT areas. Those WIP sections are associated with NVA activities.

**FIGURE 2.7**

Unit processes under review.

**FIGURE 2.8**

Bending workstation layout.

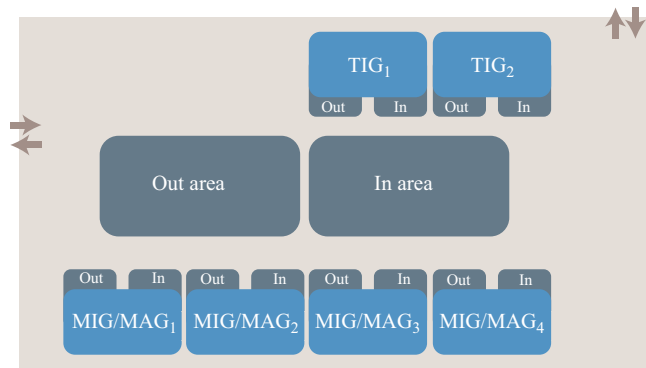
Manual welding. This unit process joins parts of a same subassembly. However, in this work it will be considered that this generates the final products. This process could be executed in either of two different ways: MIG/MAG or TIG welding. Because their soldering characteristics are very distinct, the kind of solder to use when planning an OF has to be defined. The manual welding section has six different machines, four that work with MIG/MAG techniques and two that follow the TIG procedure. Each one of these appliances also has its own characteristics. Its layout is expressed in Fig. 2.9. Two larger WIP areas are in the middle of the section to facilitate parts supply. Also, there exist IN and OUT spaces in each of the six machines.

Kits. This section only generates WIP since the parts produced in the bending process are stored here to make a kit. The kit contains parts of a subassembly. In this work, a kit is considered to be the final product.

The main advantage of kitting is that the material flow is simplified, as parts wait in a specific sector and do not disturb transportation inside the factory.

In order to fully evaluate the production system, the activities performed in each of the unit processes above stated will be integrated in the production system analysis whether they are NVA tasks or not. In the system's modeling, each process is divided into activities:

- *Operation:* Time needed to perform the bending action or the welding itself. In the bending and manual welding processes the operation time is part of the

**FIGURE 2.9**

Manual welding workstation layout.

whole, in the kits process the operation consists of the whole time spent in the activity;

- *Setup*: This is an NVA pure period that is required to prepare a machine, tools, or materials necessary for it to be ready to accept a new job. Regarding the sections analyzed in this work, this activity is part of both the bending and manual welding processes;
- *Waiting period*: Each workstation has a place, marked on the floor, where parts wait to go to a machine (the IN area) or to get out of the processing section (the OUT area). Regarding the sections analyzed in this work, this activity is part of both the bending and manual welding processes.

2.4.4 Indicators

In line with what is exposed in Section 2.3, with the system boundaries identification comes the selection of the most suitable indicators for the company production system.

This selection was made by taking into account the representativeness of the suggested indicators to the specific case of company A. In consequence, every company can add some new indicators or adapt these to its own strategy.

Both the bending and manual welding processes above described are subdivided into four different phases: IN area; setup time; operation; OUT area (see Fig. 2.10, where IN and OUT area times are included in waiting time). The MSM extended results, including wastes, were considered, nevertheless in the final MSM boards only the overall efficiencies are highlighted (but including these wastes).

Next, the computed indicators for each of the processes referred to above are equated and further explained. The following formulations are based on Eq. (2.1).

		Waiting	Setup	Operation	
Flow	Time	✓	✓	✓	
	Time in equipment	✗	✓	✓	
Resources	Equipment power consumption	✓	✓	✓	
	Workers usage	✗	✓	✓	

FIGURE 2.10

Manual welding workstation layout.

2.4.4.1 Flow indicators

Time: The time planned is defined by the company for a specific job according to the company's cadence and production level, and is assigned only to the operation task and excludes setup and storage times (which is the time of the VA activity).

The indicator that refers to time efficiency sums up the ratio, as expressed in Eq. (2.2). The total time is the real time consumed in the operation. The total time parcel is higher than the planned time because its value also includes waste times.

$$\varphi_{time} = \frac{timeplanned[sec]}{totaltime[sec]} \quad (2.2)$$

Time in equipment: The indicator expressed by Eq. (2.3) intends to characterize the different phases of a unit process over the production flow, depending on the machine that is performing.

$$\varphi_{timeinequipments} = \frac{timeplannedformachinem[sec]}{totaltimeinmachinem[sec]} \quad (2.3)$$

In the case that the parts do not pass through a machine m , its efficiency is assumed to be maximum. Also, this indicator has only meaning in the operation and setup phases, as long as parts only spend time in a machine during their manufacture. This metric is not analyzed in the kits section because all the work there is done manually.

2.4.4.2 Resources indicators

Equipment power consumption: This refers to the electrical energy over time supplied to operate an electrical machine, which is in fact more than the amount really needed for the equipment to perform. It is important to take into account two different power values, the one that is associated with a machine performing an activity and the one that is the residual power that the machine has when idle.

The indicator referent to each equipment in a unit process is illustrated in Eq. (2.4).

$$\varphi_{equipmentpc} = \frac{machinempower[kw] * timeplannedinmachinem[h]}{totalpowerconsumptioninmachinem[kWh]} \quad (2.4)$$

On one hand, the nominator amount indicates the power consumed by a machine performing the operation itself, during the time designed for the operation phase. On the other hand, the denominator parcel that is suggested refers to the power that is effectively consumed (operation power in setup and residual power in idle time).

Workers usage: The rate of operators effectively contributing with VA activities is given by the indicator in Eq. (2.5).

$$\varphi_{Workersusage} = \frac{Workersneeded \times timeplanned[s]}{Workersscheduled \times totaltime[s]} \quad (2.5)$$

To obtain the designed value for the workers usage, the number of workers assigned to the OF operation must be assessed. The total value of workers usage stands for the number of workers that are scheduled to a unit process during the time performed. Thus, this indicator has no meaning during time that parts spend in both IN and OUT sections.

2.4.4.3 Associated costs

It is of utmost importance to control where and how a company is spending its capital, and this practice often leads to improvement actions (Baptista et al., 2015).

The cost analysis considers the specific duration of each activity based on the time indicator and makes a detailed analysis with both labor costs and each machine's associated costs.

2.5 Production system model

A discrete events simulation (DES) model was built as the production model of company A. A model in OR context is defined as “a representation of an actual object or situation. It shows the relationships (direct or indirect) and inter-relationships of action and reaction in terms of cause and effect” (MAESTRI, 2015). This factual representation consists of a vital tool for evaluating the company A business, as well as developing and comparing different strategies and observing their outcomes.

The simulation schematics used to interpret the behavior of the processes depicted was done using a toolbox called SimEvents^R. This toolbox recreates systems based on DES and is fully embedded in Simulink. This means, roughly, that the production system's model has event-driven semantics and will be focused on the effects of task timing and resource usage on its performance.

In the designed company A model, entities are OFs that are generated as the simulation starts and from an Excel file that has all the information like times, quantities, or employees needed.

There are also resources pools in the model (graphically simplified in Fig. 2.11), that control both the available machines in each unit process and the employees.

The modeling phase is implemented as a simulation-based scheduling, and that is the core of the problem which will be then optimized.

Simulation-based scheduling prefers a simulation model of the facility to the detriment of a set of mathematical constraints that define it. This approach allows the implementation “as-is” on the shop-floor without adjustments, avoiding non-optimal schedule decisions when infeasible solutions are created (Pegden, 2016). In fact, it also requires that all the data are fully known and deterministic.

2.5.1 Model description

First, a generic scheduling problem should be formalized before it is effectively modeled and analyzed. In Fig. 2.12, by resorting to the use of formal methods based on timed Petri nets, the system modeling and consequent analysis of temporal behavior can be easily achieved. Gray arrows represent different possibilities of routing an OF inside the manufacturing system.

It all starts by simultaneously generating different OFs, at simulation start. Lighter gray diamonds are decision phases that establish at least two different possible routes.

Regarding the antecedent description of the different manufacturing processes to be modeled, some differences on the machines by which they are constituted are also formalized in Figs. 2.13 and 2.14.

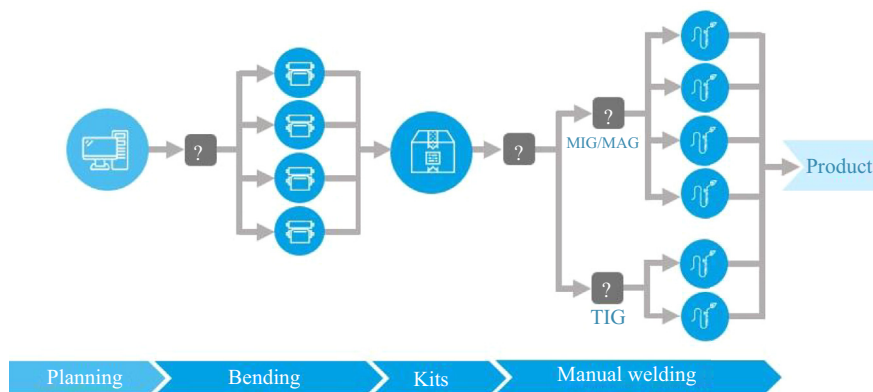


FIGURE 2.11

Model simplification.

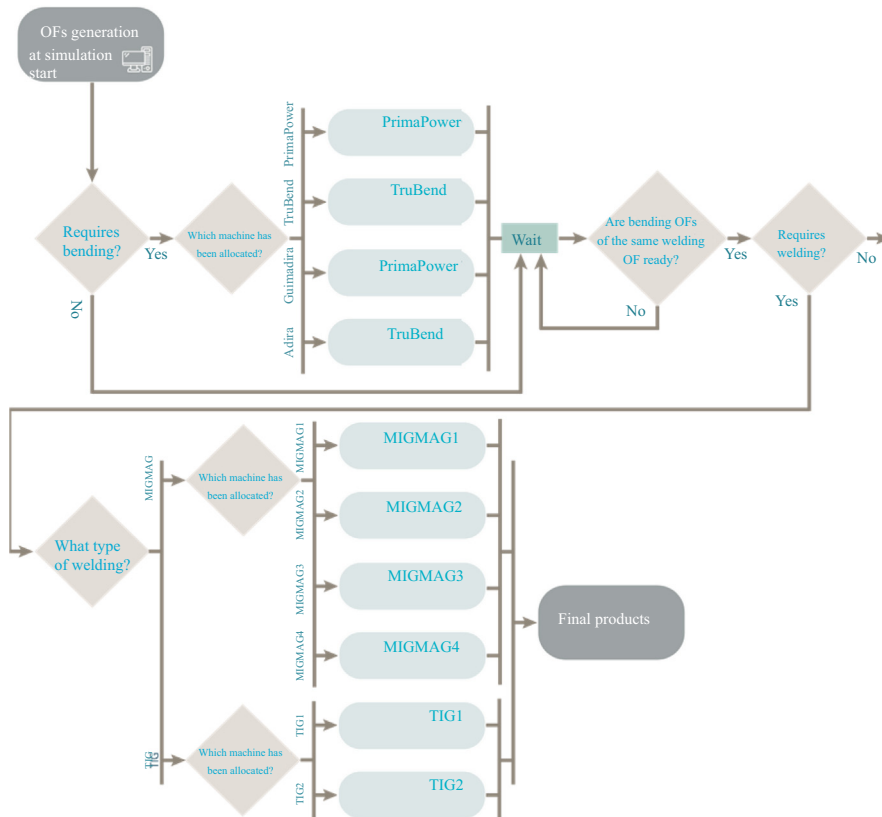


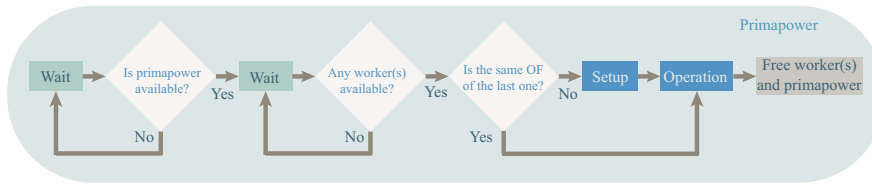
FIGURE 2.12

Production system's behavior schema assuming previous machine allocation to each OF.

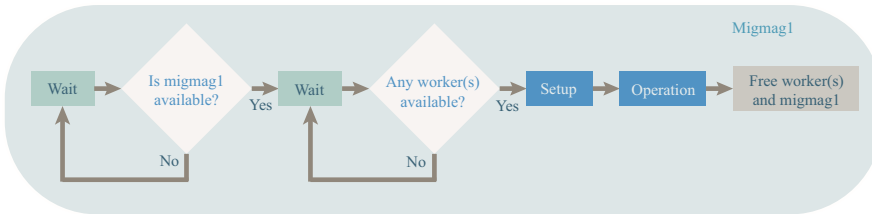
Also, a simplification of the reality is intended to promote faster understanding.

This procedure allows the study to focus on what is really important to understand. The enumeration of some assumed simplifications and constraints make the model development easier to perceive (Roshanaei, 2012):

- There is routing flexibility since operations can be processed on more than one machine, within the same process (in the case of bending) or within the same type of process (in welding);
- Pre-emption or job cancellations are not considered;
- A machine can only process one job at a time;
- Each bending machine has its own planned setup and operation times, because they are different in reality. If similar parts pass one after another, setup is only performed once;

**FIGURE 2.13**

Bending machines' behavior schema.

**FIGURE 2.14**

Welding machines' behavior schema.

- In the welding process, each type of welding operator has the same planned times;
- In the kits section there are always three employees continuously working;
- Breakdowns are not contemplated in this study;
- All jobs are inspected a priori, that is, no defective part is advised;
- Jobs are not independent because it is an assembly job shop, and therefore final products depend on the parts that constitute them. The kits section is where the OFs assembly is made;
- Order volumes are known since the planning generates the necessary OFs;
- There is no flexibility associated with setup or operation times of the same OF. Although the model is prepared for this situation, it was impossible to collect this kind of data in company A. This will directly impact both in the setup and operation efficiencies that will be in any case of maximum value;
- Transport times between different processes are considered null. This means that it will not be registered any time in the bending OUT section since all parts proceed directly to the kits section;
- Products originated in the welding process are considered to be the final products of the manufacturing system. This information will affect the time parts spend in the welding OUT section, it will be always null and its efficiency is maximum.

Specifically to the case study, it is important that the developed model comprehends volume flexibility since the model inputs can change, and the demand

may require different OF. It also applies to the need for providing the model with routing flexibility because different machines can be allocated to a specific OF in consecutive simulations.

2.5.2 Practical description

In the company A production system model, a production plan that includes the OF's waiting list is assumed to be the entity generator source. In detail, entities are OFs that the manufacturing system has not yet started. Entities are generated as the simulation starts. By reading an Excel file with the production plan's variables for each OF, it inputs information into the model. Among various other attributes, entities must record the OF number, employees that will be needed to perform the operation, the assigned machine to each job, and different planned times depending on the machine.

Also, different resources have diverse capacities that are assigned to the model based on another Excel file. This way of reading information through Excel was considered due to the current way of working in the company, that is, they have all information in Excel files.

Finally, the developed model can be configured to output information related to the entities' flow along the unit processes. There, each entity is stamped with the simulation time that it passes through key points. Resorting to the bending unit process for exemplifying (see Fig. 2.15), an entity must record both the time that it enters the IN section and the time that it exits it.

The time an entity spent in the IN section can be computed using Eq. (2.6). The same logic can be used to compute the time that entities spend in NVA activities, and which are the efficiency values that this work aims to improve.

$$\text{Time entities spent in the Bending IN section} = \text{OutBendingIN} - \text{InBendingIN} \quad (2.6)$$

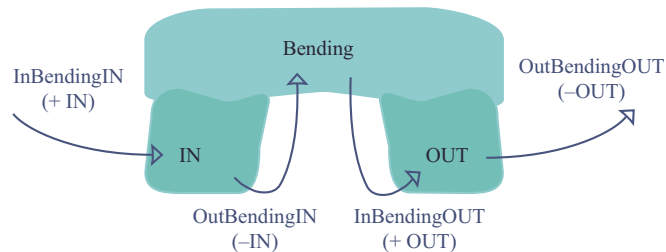


FIGURE 2.15

Bending times that are stamped into entities' attributes.

2.5.3 Model applicability

As an example, a simple OF's planning was used to test the model created. The clarity and simplicity of the data presented in [Table 2.1](#) make all results easy to visualize since it only gives origin to one final product. In the table only relevant information for the model to run is shown.

The first column specifies the OF identification and the second column which process it should go to. The employees and machine columns specify the resources that each OF needs to be produced. This tables also highlights the designed time that each OF must spend in both the setup and operation activities.

However, note that in the Excel file related to the production plan, the user must provide the planned times related to all machines (in the case of bending) or related to the types of solder technique.

Additionally, another plan (see [Table 2.2](#)) was introduced into the model, which allows comparison of both MSM results and also verifies its functionality. This plan has the same OFs but changes their attributes.

Setup times are represented in a lighter color than the operation ones over time in each of the bending machines. In the y axis are labeled the OFs that pass through the bending process, whatever the allocated machine is.

Table 2.1 OFs—Plan 1

OF	Process	Employees	Machine	Setup(s)	Operation(s)
11	Bending	1	4	197	259
12	Bending	1	3	261	334
12	Bending	1	1	253	325
13	Bending	2	2	324	482
13	Bending	2	3	338	495
21	Welding (MIGMAG)	1	1	693	758

Table 2.2 OFs—plan 2

OF	Process	Employees	Machine	Setup(s)	Operation(s)
11	Bending	1	3	185	241
12	Bending	1	3	261	334
12	Bending	1	1	253	325
13	Bending	2	2	324	482
13	Bending	2	4	447	672
21	Welding (MIGMAG)	1	1	693	758

Note that only by changing the allocated machines to each of the bending jobs, the makespan result will not be the same, as is illustrated in [Fig. 2.16](#). This little change will impact the system's behavior over time, and consequently will affect the MSM results.

In Fig. 2.16A the makespan rounds 1400 s, it is much smaller in Fig. 2.16B. This simple case expresses the huge difference between both schedules that will impact in the MSMs. However, note the impact of the makespan in MSM does not have a linear behavior in complex scheduling plans. As both example

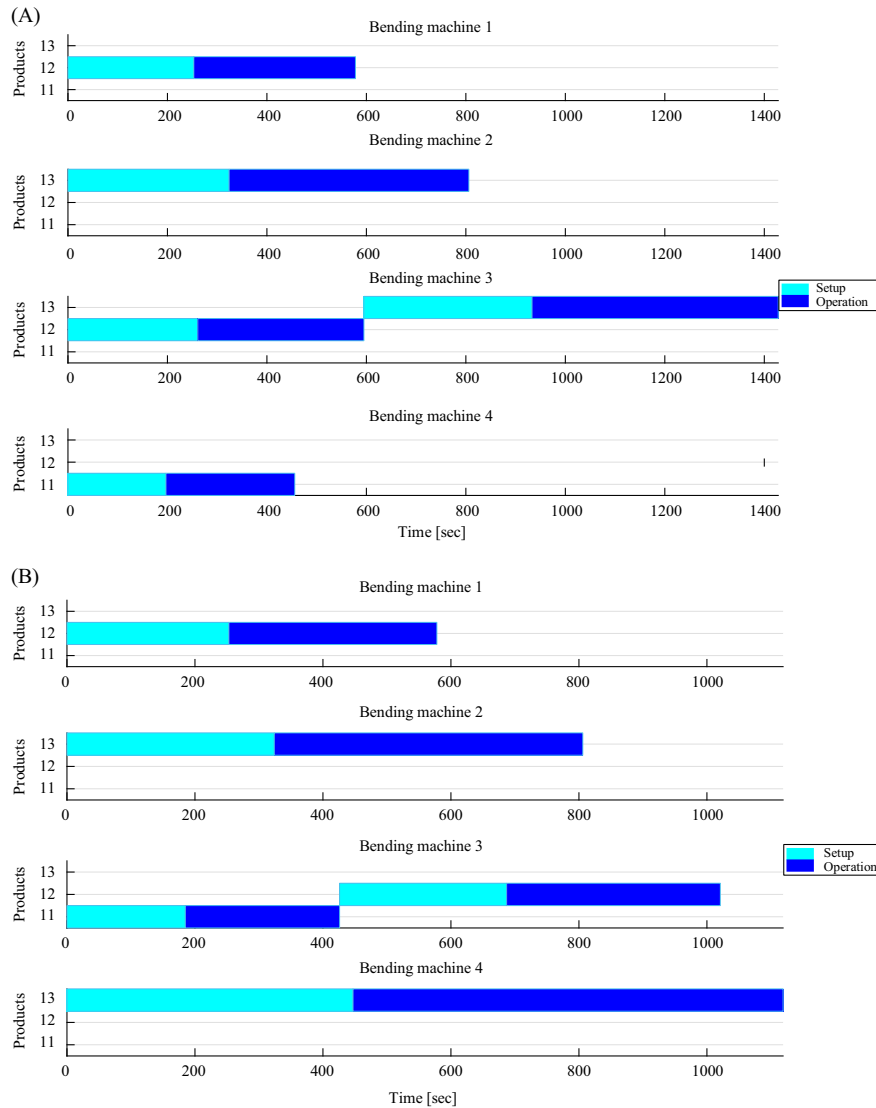


FIGURE 2.16

Comparison between bending plans' schedules: (A) bending scheduling of plan 1; (B) bending scheduling of plan 2.

production plans represent only one final product, the four first parts to be made have to wait in the kits section until the last part bending is done. This causes WIP in the kits sections and, therefore, the longer the wait, the worse the efficiency associated with this unit process.

Then, the final MSMs related to the welding OF emerge in Fig. 2.17. Since this simple plan only refers to a final product, the linear dependency of MSM with the makespan values is verified. This means that plan 2 has less inefficiencies sources than plan 1, which is intuitively verified by colors.

Many more situations were then carefully and exhaustively tested to achieve the expected results and the model was then fine-tuned to ensure that it represented the company A reality.

2.6 Optimization technique

After having the problem translated into a model, and being able to simulate different scenarios, a computer-based procedure to find promising solutions is needed. This represents the third phase of the generic OR procedure.

In fact, according to [Niazi et al. \(2006\)](#), job-shop scheduling problems are NP-complete problems due to the exponential growing search space in possible resources and goals combination. Particularly, as this case refers to an assembly job-shop problem, the search space is even larger.

The case study presented is a combinatorial problem since the intention is to optimize the scheduling mechanism. In combinatorial problems, we are looking for an object from a finite set ([Gendreau and Potvin, 2005](#)). Therefore it intends to minimize NVA activities such as the kits process itself and time that parts spend in both the IN and OUT areas.

In practice, a vector inspired by [Wang et al. \(2011\)](#) was developed to feed the model with the respective machine's allocation. Discrete variables encode the solution for the scheduling problem, as clarified in [Fig. 2.18](#).

The vector represented can be subdivided into two different sections that correspond to each process. Then, each entry of the vector refers to the machine allocated to an OF. In other words, [Fig. 2.18](#) suggests that the first OF goes to machine 2 in the bending process and to machine 3 in the welding one. Similarly, the second listed OF proceeds to machine 1 in both bending and welding processes, and so on to other OFs.

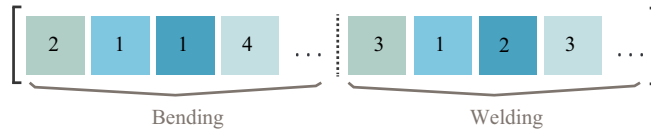
2.6.1 Heuristic approaches

A solution to this problem can be quickly found by using ad hoc techniques or by following well-known methods that have produced efficient solutions to similar problems ([Alsuwaiyel, 2003](#)).

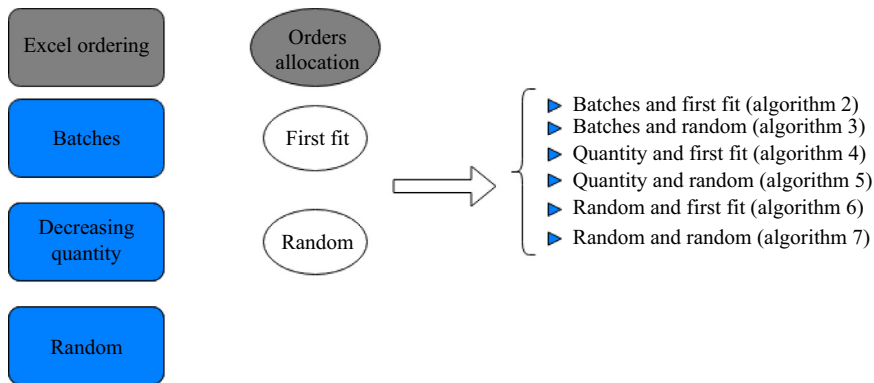
(A)		OF : 21			
		MSM			
		Bending	Kits	Welding	
Flow	Flow overall efficiency	95%	38%	100%	78%
	Time [sec]	91%	38%	100%	76%
	Equipment [sec]	100%		100%	100%
Resources	Resources overall efficiency	94%		100%	97%
	Equipment power consumption [kWh]	88%		100%	94%
	Workers usage [sec]	100%		100%	100%
Cost overall efficiency		99%	38%	100%	79%
(B)		OF : 21			
		MSM			
		Bending	Kits	Welding	
Flow	Flow overall efficiency	97%	76%	100%	91%
	Time [sec]	95%	76%	100%	90%
	Equipment [sec]	100%		100%	100%
Resources	Resources overall efficiency	96%		100%	98%
	Equipment power consumption [kWh]	93%		100%	96%
	Workers usage [sec]	100%		100%	100%
Cost overall efficiency		99%	76%	100%	92%

FIGURE 2.17

Comparison between the plans' MSMs [MSM KPIs values were calculated using Eqs. (2.1)–(2.5)] and simulation model output by using plan 1 and plan 2 OF configurations (Tables 2.1 and 2.2): (A) MSM of plan 1; (B) MSM of plan 2.

**FIGURE 2.18**

Vector schema with assigned machines to each OF.

**FIGURE 2.19**

Heuristics developed.

Traditional approaches to scheduling problems depend heavily on dispatching rules and knowledge-based systems. The disadvantage with such dispatching rules is that there is no single rule that will be effective for all production conditions, and manual selection or updating is required when using rules (Niazi et al., 2006).

The most important part of any heuristic, in this context, is to order the information coming from the Excel, that is, the order of the OFs in the production plan. To this end, three different approaches are used: ordering by batches; by decreasing demanding quantity of each OF; and random order. Then, to assign each job to a machine, first fit heuristic and random assigning are used. These heuristic's approaches (view schema in Fig. 2.19) were developed and applied to the problem.

2.6.2 Genetic algorithm

The genetic algorithm (GA) is arguably the most well-known and most used evolutionary computation technique (Boussaïd et al., 2013). The discrete variable

handling is remarkably important because this case study is a combinatorial problem, in which the aim is to optimize the machine allocation to each job, as explained by means of Fig. 2.18.

A GA is a stochastic method that uses evolutionary concepts to find better solutions in a search space. It uses a population of solutions that is changed to create the next population, also called offspring. As previously mentioned, GA has three main steps: selection, responsible for picking up solutions and creating a parent population; crossover, which combines the parent population and creates offspring; and mutation, which randomly changes individuals in the hope of finding good traits. Fig. 2.20 illustrates these steps, in a cycle. Those operators are regulated by parameters that tune the intensity of their produced effect.

The native *ga* function of MatLab was used, changing some parameters such as population size, number of iterations, or genetic operators parameters. Foremost, randomly generated solutions constitute the initial population.

This algorithm then uses three different offspring populations. The first consists of the individuals with best fitness values—the elite, limited to two. The other two offspring populations are for crossover and mutation operators.

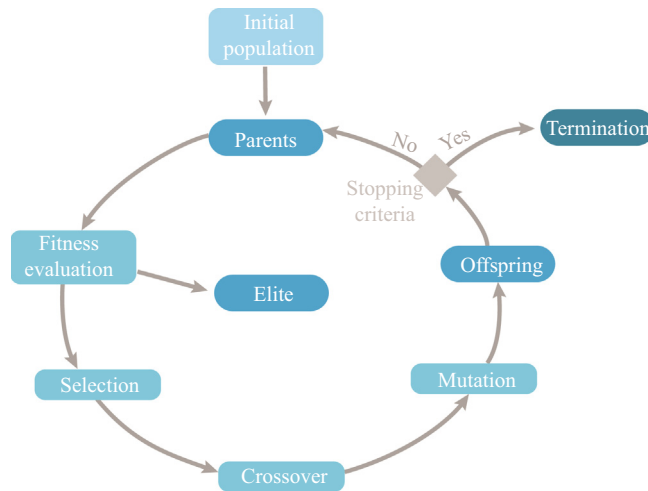
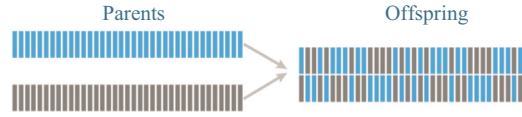


FIGURE 2.20

Generic GA's operators procedure

Adapted from Boussaïd, I., Lepagnot, J., Siarry, P., 2013. A Survey on Optimization Metaheuristics, vol. 237. Elsevier B.V.

**FIGURE 2.21**

Crossover operation schema.

**FIGURE 2.22**

Mutation operation schema.

Random selection occurs to pick solutions to go through crossover and mutation. The specific operator chosen is uniform crossover, as illustrated in Fig. 2.21, which randomly selects one vector entry from one of the parents, to all entries. A fixed probability of 50% is used, meaning both parents contribute to the same amount of vector entries.

The mutation genetic operator provides diversity and enables the GA to search a broader space. It starts also by randomly selecting an individual to change it. Uniform mutation was chosen, which randomly selects a gene and replaces it by a uniform random value between the lower and upper bounds of the solution vector (Koll and Mathworks, 2016), as exemplified in Fig. 2.22.

This corresponds to the phase of assigning machines to each the OFs in the production plan. However, first some way of ordering the production plan can be applied.

2.7 Acquired results

In the previous section, the optimization techniques approached need to be evaluated in the solution performance. A cost function was established and is given in Eq. (2.7).

$$F = 0.2 \times ((1 - \varphi_{timeBIN}) + (1 - \varphi_{timeBOUT}) + (1 - \varphi_{timeK}) + (1 - \varphi_{timeWIN}) + (1 - \varphi_{timeWOUT})) \quad (2.7)$$

The function tries to maximize the time indicator efficiency (Eq. 2.2) as an average of every manufacturing order in the manufacturing plan. In the defined cost function, $\varphi_{timeB_{IN}}$ represents the average efficiency for the bending IN section, $\varphi_{timeB_{OUT}}$ the average efficiency for the bending OUT section, φ_{timeK}

represents the average efficiency for the kits section, $\varphi_{timeWIN}$ represents the average efficiency for the welding IN section, and finally $\varphi_{time}W_{OUT}$ represents the average efficiency for the welding OUT section.

2.7.1 Heuristics

Resorting to the heuristic's approaches presented earlier, the model was tested 50 times. The exception goes to algorithm 4 heuristic which has a unique solution, since it is completely deterministic.

The fitness values of the cost function, Eq. (2.7), are plotted in Fig. 2.23a which shows a wide range of final values to the assigned cost function. In Fig. 2.23b, the same results are visualized in a box plot, allowing the variance to be visualized.

After testing the model 50 times, algorithm 5, displayed in green in Fig. 2.23, proves to be the algorithm that reaches not only the best results overall but also the lowest median value.

The best fitness value obtained for each of the algorithms can be consulted for better visualization in Table 2.3.

However, and only to give an idea of how the heuristics perform, two different solutions are presented in Figs. 2.24 and 2.25. Both plots only represent the bending unit process part of the solution, to make the perception easier. OR teams frequently use this kind of procedure because they are based on simple rules and therefore they are visually perceptible.

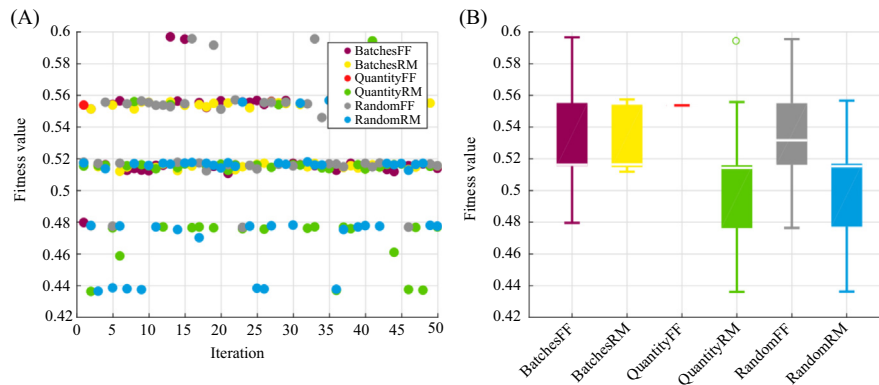
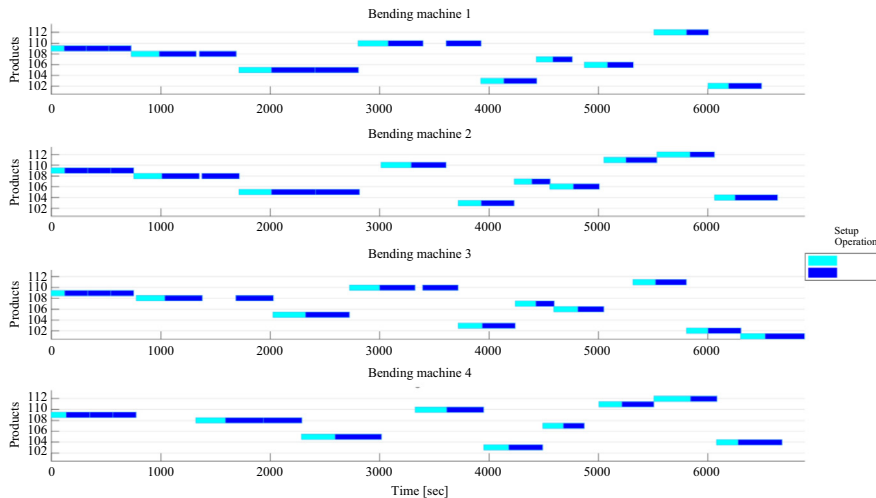


FIGURE 2.23

Fitness values for different heuristics, along 50 iterations: (A) fitness values, (B) variance analysis of the fitness values.

Table 2.3 Best heuristics fitness values [values obtained using Eq. (2.7)]

Algorithm 2	$F = 0.4796$
Algorithm 3	$F = 0.5119$
Algorithm 4	$F = 0.5537$
Algorithm 5	$F = 0.4361$
Algorithm 6	$F = 0.4765$
Algorithm 7	$F = 0.4363$

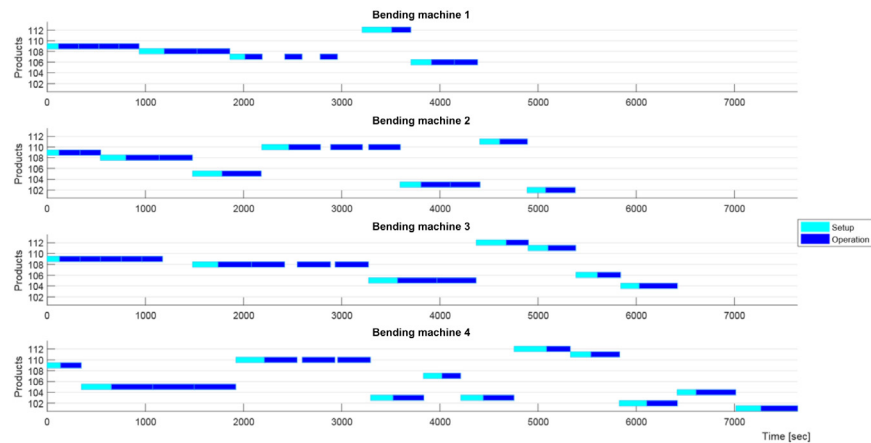
**FIGURE 2.24**

Possible scheduling result in the bending section, precedent of algorithm 4.

First, the manufacturing plan is organized starting in the OF that has greater demand and finishing in the less demanding OF. Then, in Fig. 2.24, OFs are assigned to the first idle machine in the unit process, which usually means that machines will almost register no idle times. This fact does not occur when the limit of employees is reached for the unit process, and the white spaces in the plots are stops which result from a lack of employees.

In contrast, outlining the top-performing heuristic in Fig. 2.25, although the manufacturing plan input to the model is the same, OFs are randomly assigned to unit process machines. This causes huge discrepancies in the throughput time for each of the machines on disposal, but the overall fitness value is the best.

Consequently, and as already said, while in algorithm 4 the makespan rounds the 6500 seconds, resorting to algorithm 5 the makespan results above 7000 seconds, which is considerably worse regarding the makespan. However, the MSM's indicators do not depend only on the bending process makespan,

**FIGURE 2.25**

Possible scheduling result in the bending section, precedent of algorithm 5.

and therefore it is possible that a solution with worse makespan yields better MSM indicators.

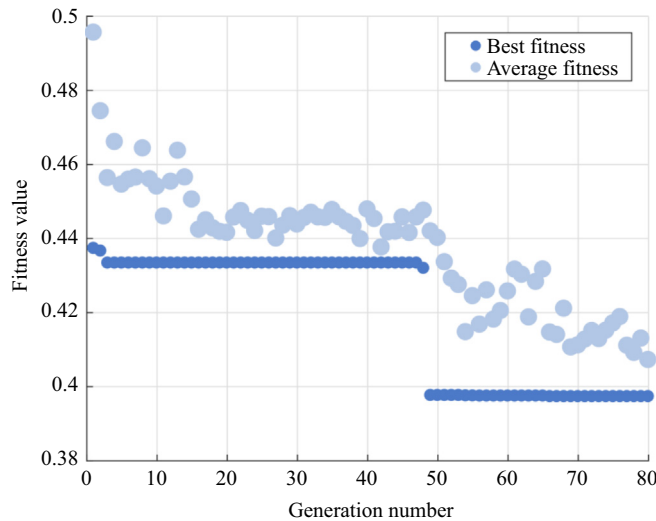
In addition, optimization of the scheduling process to improve some MSM metrics results in a more sophisticated problem. Instead of optimizing the system only in terms of the makespan metric as classical job-shop problems do, it resorts to many variables based on time and computes the indicators that comprise the cost function. Therefore it is not easy to see improvements in this kind of plot with the naked eye.

2.7.2 Genetic algorithm strategy

The same analysis is now made using the GA algorithm. The model input is the manufacturing plan that was also imposed to the system in the best heuristic registered and consists of ordering the OFs in a decreasing way regarding the quantity to be produced.

In Fig. 2.26 it is possible to verify the metaheuristics' power, in particular of the GA, which shows the evolution of the population's best and average fitness function across all generations. The outlined behavior of the computed cost function value reveals that metaheuristics can overcome local optimal values. In other words, the stair behavior is typical when the search for a suboptimal solution is performed with metaheuristics techniques.

The best result yielded from a single run of GA is slightly below $F = 0.4$, which means that it hugely improves the heuristic result which is $F = 0.4361$. As expected, the metaheuristic approach performs better than all the heuristics defined. The next section formalizes this comparison.

**FIGURE 2.26**

Fitness values using the GA, along 80 generations and with a population of 20 individuals.

2.7.3 Optimization approaches enforcement

Resorting to optimization techniques is crucial in the decision-making process to provide suboptimal solutions that have reasonable performance. The comparison between classical heuristics and metaheuristics is now performed using the MSM's metrics.

Additionally, scenarios will be simulated simply by changing the cost function in the GA approach.

2.7.3.1 Comparison between the applied heuristics and GA

To establish the algorithms comparison, only the best heuristic and GA methods are considered. To make this analysis in the light of the MSM methodology, its metrics overall results are set side by side.

Keeping in mind that MSM only refers to one final product, to make a global comparison between both the heuristics and GA approaches, the MSM tool that represents the average efficiency of all final products has to be enunciated.

In Fig. 2.27, the average result using the best heuristic of the final product's MSM is outlined. Some inefficiencies are apparent along the unit processes.

Now looking at the GA's results, in Fig. 2.28, the MSM's metrics improve regarding the provided cost function. The effects on the indicator values are more perceptible in the rightmost column and in the welding column.

OF : Average		MSM			
		Bending	Kits	Welding	
Flow	Flow overall efficiency	59%	12%	97%	56%
	Time [sec]	18%	12%	95%	41%
	Equipment [sec]	100%		100%	100%
Resources	Resources overall efficiency	56%		90%	73%
	Equipment power consumption [kWh]	13%		80%	46%
	Workers usage [sec]	100%		100%	100%
	Cost overall efficiency	63%	12%	80%	52%

FIGURE 2.27

Final MSM that results from the best heuristic.

Therefore, and as expected, the MSM's metrics improved as the cost function value decreased. It is thus proven that using the GA in combination with the MSM's metrics is a promising approach, reaching better results than any classical heuristic.

2.7.3.2 Simulating scenarios

Besides the improvements in efficiency values, using the GA also allows improvement of the MSM's metrics in relation to specific scenarios. Some real impasses that OR teams face are mentioned here and therefore the possible direction that the company's strategy should follow is analyzed.

Using the initial production plan provided by the best heuristics, two different scenarios are simulated, the first where a whole-process MSM metrics is meant to be prioritized, and the second where the same happens but for a specific product.

OF : Average		MSM			
		Bending	Kits	Welding	
Flow	Flow overall efficiency	56%	10%	100%	55%
	Time [sec]	12%	10%	100%	41%
	Equipment [sec]	100%		100%	100%
Resources	Resources overall efficiency	54%		100%	77%
	Equipment power consumption [kWh]	9%		100%	54%
	Workers usage [sec]	100%		100%	100%
	Cost overall efficiency	65%	10%	100%	58%

FIGURE 2.28

Final MSM that results from the best fitness value of the GA.

Specific *process* metrics improvement:

Suppose that a specific process should be improved since it is actually causing huge WIP quantities, for example, the bending process. A simple change in the cost function is enough to prioritize the *bending's* metrics to the detriment of other unit processes, but still taking them also into account. Therefore a new cost function is defined (Eq. 2.8).

$$F = 0.425 \times ((1 - \varphi_{\text{time}BIN}) + (1 - \varphi_{\text{time}BOUT})) + 0.005 \times ((1 - \varphi_{\text{time}K}) + (1 - \varphi_{\text{time}WIN}) + (1 - \varphi_{\text{time}WOUT})) \quad (2.8)$$

In the defined cost function, $\varphi_{\text{time}BIN}$ represents the average efficiency for the bending IN section, $\varphi_{\text{time}BOUT}$ represents the average efficiency for the bending OUT section, $\varphi_{\text{time}K}$ represents the average efficiency for the kits section, $\varphi_{\text{time}WIN}$ represents the average efficiency for the welding IN section, and finally $\varphi_{\text{time}WOUT}$ represents the average efficiency for the welding OUT section.

OF : Average		MSM			
		Bending	Kits	Welding	
Flow	Flow overall efficiency	59%	26%	99%	61%
	Time [sec]	19%	26%	98%	47%
	Equipment [sec]	100%		100%	100%
Resources	Resources overall efficiency	57%		90%	74%
	Equipment power consumption [kWh]	13%		81%	47%
	Workers usage [sec]	100%		100%	100%
	Cost overall efficiency	64%	26%	81%	57%

FIGURE 2.29

Final MSM that results from Eq. (2.8) optimization.

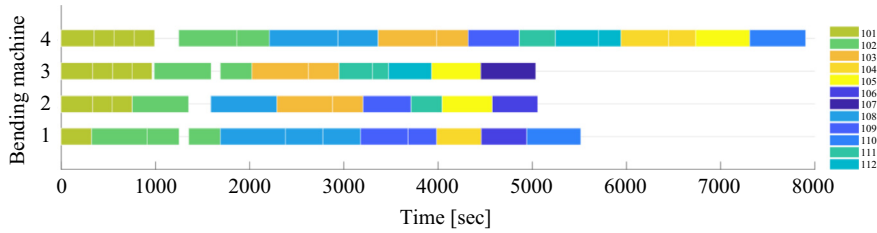
The resulting MSM's metrics are outlined in Fig. 2.29.

In this case, visual perception of the improvement is not instantaneous. However, regarding the bending unit process, some metrics values were improved when compared with the GA used in combination with the MSM's metrics in Fig. 2.28.

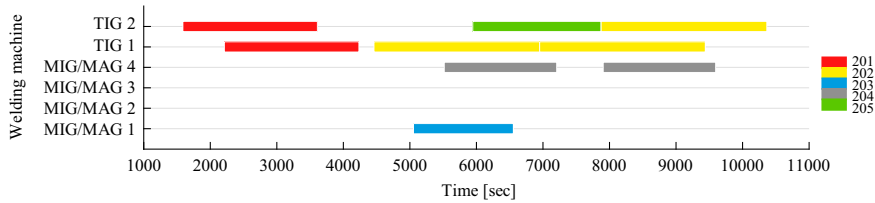
Therefore it is proven that using the GA also allows control to prioritize a particular unit of the process, since the bending's MSM metrics were improved. The same effect could be achieved for any other process, such as welding or kits, simply by assigning more weight to these processes in the cost function in Eq. (2.8).

The model outputs the best scheduling practice for easy visualization, both for bending scheduling (see Fig. 2.30) and welding (Fig. 2.31).

These scheduling solutions are harder to implement than those obtained by heuristics, because they require significant manufacturing flexibility. Nevertheless, using the MSM's metrics these are the best found solutions.

**FIGURE 2.30**

Solution to be implemented in the *bending* unit process, after optimization with the cost function in Eq. (2.8).

**FIGURE 2.31**

Solution to be implemented in the *welding* unit process, after optimization with the cost function in Eq. (2.8).

Specific *products* metrics improvement:

The second tested scenario represents the need for improving the MSM's metrics of a specific final product. This may occur if a client orders with urgency, for example. Using the final product with OF 203, the cost function is once again changed to prioritize all products stamped with that OF, as in Eq. (2.9).

$$F = 0.2 \times ((1 - \varphi_{\text{time}B_{IN}, P3}) + (1 - \varphi_{\text{time}B_{OUT}, P3}) + (1 - \varphi_{\text{time}KP3}) + (1 - \varphi_{\text{time}W_{IN}, P3}) + (1 - \varphi_{\text{time}W_{OUT}, P3})) \quad (2.9)$$

The function tries to maximize the time indicator efficiency (Eq. 2.2) for manufacturing order 203. In the defined cost function, $\varphi_{\text{time}B_{IN}, P3}$ represents the average efficiency for the bending IN section, $\varphi_{\text{time}B_{OUT}, P3}$ represents the average efficiency for the bending OUT section, $\varphi_{\text{time}KP3}$ represents the average efficiency for the kits section, $\varphi_{\text{time}W_{IN}, P3}$ represents the average efficiency for the welding IN section, and finally $\varphi_{\text{time}W_{OUT}, P3}$ represents the average efficiency for the welding OUT section.

The MSM's metrics that result from the attempt to improve only one final product's efficiencies are displayed in Fig. 2.32, showing only the respective OF values. For comparison purposes, the MSM of OF 203 for the final solution obtained using Eq. (2.7) is also illustrated in Fig. 2.33.

The maximization of an objective function that improves the performance of the specific product as a result increased some of the MSM indicators, namely a fair increase in the bending overall efficiency, and an 11% increase of the bending cost efficiency.

In this scenario, the case of trying to improve exclusively the metrics of one final product, the model outputs the best scheduling practice for easy visualization in both bending (Fig. 2.34) and welding scheduling (Fig. 2.35).

This procedure proves again the great advantages in adopting different production strategies, combining metaheuristics with the MSM to reach better product scheduling. Classical OR teams employ heuristic procedures in real-life machine allocation.

Indeed, this solution is difficult to implement because it evolves assigning batches in a discontinuous manner to each machine. In this case study, it can

OF : 203		MSM			
		Bending	Kits	Welding	
Flow	Flow overall efficiency	55%	31%	100%	62%
	Time [sec]	9%	31%	100%	47%
	Equipment [sec]	100%		100%	100%
Resources	Resources overall efficiency	53%		100%	77%
	Equipment power consumption [kWh]	7%		100%	53%
	Workers usage [sec]	100%		100%	100%
	Cost overall efficiency	52%	31%	100%	61%

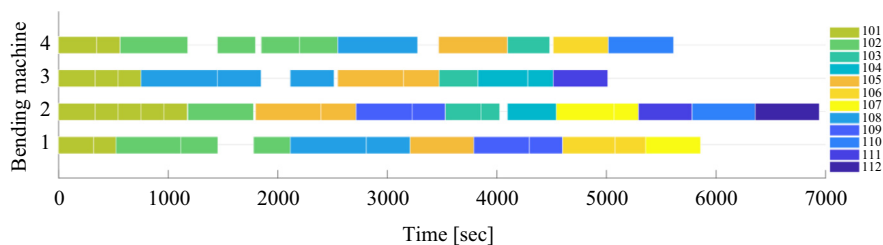
FIGURE 2.32

Final MSM that results from Eq. (2.9) optimization.

		MSM			
		Bending	Kits	Welding	
Flow	Flow overall efficiency	53%	5%	100%	53%
	Time [sec]	7%	5%	100%	37%
	Equipment [sec]	100%		100%	100%
Resources	Resources overall efficiency	53%		100%	76%
	Equipment power consumption [kWh]	5%		100%	53%
	Workers usage [sec]	100%		100%	100%
	Cost overall efficiency	43%	5%	100%	50%

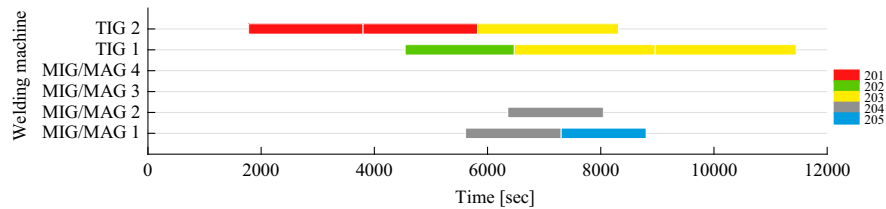
FIGURE 2.33

Final MSM that corresponds to the best GA fitness value to OF 203, using Eq. (2.7).

**FIGURE 2.34**

Solution to be implemented in the bending unit process, after optimization with the cost function in Eq. (2.9).

be easily implemented by company A since the company already instructs a team leader per unit process to distribute the WIP that each machine should perform.

**FIGURE 2.35**

Solution to be implemented in the welding unit process, after optimization with the cost function in Eq. (2.9).

2.8 Conclusions

This work was proposed to optimize some characteristics inside an industrial environment that will impact on the MSM's performance improvement. This concept came to support the decision-making process, allowing comparison of different strategies immediately before their implementation on the shop-floor.

The use of MSM based on an IoT platform is recommended to assure the correct permanent feed of trusted data. In addition, a methodology is proposed to use MSM assessment to improve the production system performance. This methodology is based on discrete event simulation and a metaheuristic optimization technique that proposes optimal solutions to improve the MSM indicators, meaning the way the production should be planned to increase overall efficiency. The decision-maker can adapt the objective or cost function to the anticipated needs, and the methodology will give the best production configuration to maximize this. In this way the high potential of MSM is enhanced and better aligned with the Industry 4.0 trend: it gives a full real-time mapping of production system efficiency performance and allows the user to find alternative solutions to mitigate critical aspects.

The presented work focused mainly on applying the concept to a real case study. The MSM methodology was applied to this work and the resulting improvements are due to optimizing the scheduling process in the bending, kits, and welding processes. The fact that this work brings novelty to MSM methodology applications also means that it is an embryonic work and much more remains to do in this direction.

Acknowledgments

This work was supported by FCT, through IDMEC, under LAETA, project UID/EMS/50022/2019.

The authors gratefully acknowledge the funding of Project POCI-01–0247-FEDER-017637, cofinanced by Programa Operacional Competitividade e Internacionalização and Programa Operacional Regional de Lisboa, through Fundo Europeu de Desenvolvimento Regional (FEDER) and by National Funds through FCT—Fundação para a Ciência e Tecnologia.

The authors also gratefully acknowledge the funding of Project POCI-01–0247-FEDER-024541, cofinanced by Programa Operacional Competitividade e Internacionalização and Programa Operacional Regional de Lisboa, through Fundo Europeu de Desenvolvimento Regional (FEDER) and by National Funds through FCT—Fundação para a Ciência e Tecnologia.

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A probabilistic approach to reconfigurable interactive manufacturing and coil winding for Industry 4.0

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3.1 Introduction

During the last few years, the dissemination of robots has exploded in many areas of daily life. Robotic devices can now be encountered not only in the most advanced factories, but also in our homes. Nowadays, it is common to find a robot autonomously cleaning up a house, or assisting a surgeon during a medical operation. A

key factor for the Industry 4.0 upgrade is the use of robots (Hagele et al., 2008). Nowadays, manipulators are employed for supply chains in which the same task is accomplished several times in a repetitive manner. The main reasons are the price decrease and the boosted investments to develop technology in the field of robotics. All these new technologies have the goal of improving peoples' quality of life, for example, by reducing their workload, or by replacing the operator in dangerous and strenuous tasks. In the majority of cases, human operators can understand easily how to perform the task even in complex situations, but they have not the expertise to program a robot. A useful solution could be obtained if the operator would be able to teach the robot how to perform a certain task, guiding the robot or showing himself what to do using a Robot Learning by Demonstration paradigm (Billard et al., 2008). Also known as Robot Programming by Demonstration, this paradigm aims to train robotic devices through human demonstrations in order to teach them how to perform a task (Calinon and Billard, 2007b) and many examples in the literature illustrate the useful aspects of applying robot learning by demonstration techniques to provide an easy way to program robots (Dillmann, 2004).

Up to now, several research groups have developed different paradigms and techniques, but only a limited number of attempts have been made in real industrial environments. Myers et al. (2001) wanted to automatically insert a PC card into a backplane slot on the motherboard treating forces/moments as the sensed inputs and robot velocities as the control outputs. Baroglio et al. (1996) believed that the robot's ability to gain profit from its experiences is crucial for fully exploiting its potential. They analyzed several approaches and tested them in a classical industry-like problem: inserting a peg into a hole. The task was performed while recovering from error situations, in which, for instance, the peg is stuck midway because of a wrong inclination. Neto et al. (2010) presented a way to program a robot showing it what to do by using gestures and speech. The gestures are extracted from a motion sensor, namely a Wii remote controller. The Japanese company Fanuc is developing robots that use reinforcement learning to train themselves (Knight, 2016). Fanuc's robot learns how to pick up objects while capturing video footage of the process. The new knowledge is used to refine a deep learning model that controls robot actions. It has been proved that after about 8 hours the robot reaches up to 90% accuracy or above, almost the same as if it was programmed by an expert.

Usually, robots need a large number of demonstrations to learn how to perform a simple task. Selecting a specific machine learning algorithm could help to reduce the number of demonstrations in certain contexts, but otherwise improvements are limited. On the other hand, overcomplicated machine learning algorithms could end in overfitting. Consequently, the model could fail in predicting reliably future observations. The same problem may occur when data are limited and the model focuses on specific situations without the possibility to fit additional data. With overfitting, the framework lacks abstraction and generalization capability and will not be able to face even limited variations. Generalization is a key concept if the goal is to obtain a relation between robot movements and the objects to be manipulated during the task. Nevertheless, very simple algorithms

coupled with an excessively wide data set could lead to underfitting. The resulting model will not capture the common characteristics among the data providing poor predictive performance. A good way to incorporate variability is to consider actions performed by many different subjects (Matsubara and Morimoto, 2013). The same gesture can slightly change depending on who is doing the movement. The gesture remains correct, but the ways to perform it are almost infinite. However, the risk of underfitting is forestalled since there are common characteristics among the numerous ways different subjects perform the same movement.

In kinesthetic demonstration (Calinon et al., 2007), the robot is physically guided through the task by humans. An alternative approach could be learning from visual information (Michieletto et al., 2013). In fact, the constraints characterizing the movement should be extracted from a sequence of images. Furthermore, industrial applications require particular conditions on safety and efficiency. These aspects have to be taken into account when building the model to control a robotic device. The advent of Industry 4.0 brought new and innovative challenges (Lasi et al., 2014) for robotics. The new concept of Industry 4.0 aims at reducing waste, while maximizing the customization of the product, therefore a flexible and dynamic production line is essential. An efficient method of production is necessary in modern factories, and the manufacturing system should be able to switch production in a very short time. The presence of intelligent and collaborative robots is a key factor for the fulfillment of these targets. Old-fashioned robots are expensive devices, closed in a cage, repeating continuously the same task. Reprogramming one of these robots takes time and money, and requires the intervention of specialized programmers. New robots are lightweight and no longer closed in cages, since they are equipped with force sensors, aware of possible contacts with the surrounding world. The characteristics of collaborative robots (cobots) make them ideal to be programmed by demonstration. This programming paradigm reduces the time needed to program the robot, since there is no requirement for specialized personnel. On the contrary, the machine will learn the task by observing the demonstrations performed by skilled workers, who know well the tasks the robot should do. Furthermore, cobots offer the possibility of having humans and machines working on the same workplace, and also to operate together to fulfill the same task. The closeness of the machine to humans creates several safety problems. The main issue is to avoid accidental contact among humans and robots. Giving robots the capabilities to perceive, understand, and react to what happens in the environment will become essential in the factories of the future. In other words, the robot should be intelligent, capable of interpreting feedback from outside, and will need the ability to understand and predict human movements.

In this chapter, we describe how variability can be considered and mathematically described as part of the problem to obtain a flexible robotic solution by applying Robot Programming by Demonstration to a real industrial case. In particular, two main use cases will be introduced: (1) the automatic assembly of a car door with its module, and (2) boosting the production of electric motor coils, by automatizing the copper winding procedure. These cases were part of a European challenge aiming to encourage collaboration between academic and industrial counterparts (Siciliano et al., 2014).

This challenge aims to boost the collaboration between research and industrial partners, in order to achieve innovative results. The remainder of the chapter is structured as follows. [Section 3.2](#) presents the general probabilistic approach and the mathematical formulation of the learning framework. The first case study regarding the automatic assembly of a car door with its module is described in [Section 3.3](#). Meanwhile, [Section 3.4](#) enters into details of the second case study in which we robotized the manufacturing process for winding coils for stator or rotor cores in electric motors. Finally, in [Section 3.5](#), we summarize the work and the achieved results.

3.2 Probabilistic framework

The learning framework proposed in this work aims at estimating the control model of a robotic device (output data) starting from human information (input data) to create a flexible probabilistic approach for reconfigurable interactive manufacturing. Data undergo a preprocessing phase in order to remove artifacts and noise from signals. After preprocessing, two main phases can be recognized, that is, an offline and an online elaboration. During the offline phase, data are collected from many subjects while performing a certain task. In this phase, the information available for each trial should contain both input and output data. A probabilistic model is trained in order to represent the processed information with a limited set of parameters. The online phase considers data directly acquired from the environment, exploiting the model previously computed to estimate the corresponding robot motion. In the following, all the concepts introduced so far are accurately described.

3.2.1 Signal processing

Selecting an extremely sophisticated machine learning technique does not guarantee high accuracy in data estimation. The aim of the preprocessing procedure is to obtain a set of significant features to estimate or in some cases predict robustly and online the movement performed by a subject. In fact, the process of filtering the significant information from input signals can affect the actual success of the entire framework. The preprocessing phase is essential to obtaining a well-balanced combination of similarity and variability within the signal. On one hand, if the considered signals have nothing in common, the final model would not work properly. On the other hand, a certain amount of variability should be integrated in the system, in order to build a general model which can work with new, unseen data.

3.2.1.1 Smoothing and normalization

Depending on the specific case study, the information collected can undergo different kinds of preprocessing. However, it is very likely that input data are very jagged and

not good enough to be used to build good probabilistic models, since the great variability of the signal results in poor model performances. Therefore a simple procedure to be applied to signals with the aim of obtaining better and more robust models consists of a combination of smoothing and normalization.

The smoothing function is based on a moving average filter. At the instant t , the average of S data points available within the windows is computed in order to smooth the data. This process is equivalent to low-pass filtering, with the response of the smoothing given by Eq. (3.1)

$$\gamma_s(t) = \frac{1}{S+1} \sum_{s=1}^S \gamma(t-s) \quad (3.1)$$

The smoothing function performs a local regression using weighted linear least squares and a second-degree polynomial model.

Differences in the amplitude and in the mean of the signal require the application of a normalization technique. The normalization process ensures the regularization of the signal in order to obtain a more robust model. The normalization has been implemented in two different manners for training and testing phases. Since the training phase is executed offline, the normalization has been accomplished by using the relative maximum within the specific trial involved in the process. Instead, during the online testing procedure the information about the relative maximum is not available. We needed to use a different method to be able to compute the normalization online. For obtaining this result, the mean of the relative maximums collected during the entire training set has been used as the normalization factor.

3.2.2 Gaussian mixture model

The Gaussian mixture model (GMM) is a parametric probabilistic model that assumes all data points are generated from a mixture of a finite number of Gaussian distributions. These distributions completely characterize the model, therefore it is composed of a weighted sum of Gaussian components. In particular, three parameters for each Gaussian component are sufficient to represent the whole of the information: *mean*, *covariance*, and *weight*. These parameters are estimated from training data using the iterative expectation maximization (EM) (Dempster et al., 1977) algorithm. EM is a statistical algorithm that iteratively finds locally maximum likelihood parameters of a probabilistic model when equations cannot be solved directly. The locally maximum likelihood is obtained repeating cyclically two phases.

The *expectation* (E) step creates a function for the expectation of the log-likelihood evaluated using the following estimate of the component parameters:

$$p_{k,k}(t+1) = \frac{\pi_k(t)N(\zeta_j; \mu_k(t), \Sigma_k(t))}{\sum_{i=1}^K \pi_i(t)N(\zeta_j; \mu_i(t), \Sigma_i(t))} \quad (3.2)$$

Maximization (M) computes parameters maximizing the expected log-likelihood found during the last *E* step:

$$\begin{aligned}\pi_k(t+1) &= \frac{1}{N} \sum_{i=1}^N p_{k,j}(t+1) \\ \mu_k(t+1) &= \frac{\sum_{i=1}^N p_{k,j}(t+1) \xi_k}{\sum_{i=1}^N p_{k,j}(t+1)} \\ \Sigma_k(t+1) &= \frac{\sum_{i=1}^K p_{k,j}(t+1) (\xi_j - \mu_k(t+1)) (\xi_j - \mu_k(t+1))^T}{\sum_{i=1}^N p_{k,j}(t+1)}\end{aligned}\tag{3.3}$$

The result is a continuously improving adaptation to the best representation of the input data as is shown in Fig. 3.1. The EM loop stops when the increment of the log-likelihood $L = \sum_{j=1}^N \log(p(\zeta_j|0))$ at each iteration becomes smaller than a defined threshold e , that is, $\frac{L(t+1)}{L(t)} < e$.

A possible limitation in the learning process is the fact that EM requires a priori specification of the number of Gaussian components K . Selecting the correct K is a crucial task. On one hand, an overestimation of this parameter might lead to overfitting and, consequently, to a poor generalization. On the other hand, an underestimation will result in poor predicting performances. Several entropy-based model selection techniques have been proposed in the literature to estimate this parameter [e.g., Bayesian information criterion (BIC) (Schwarz, 1978), Akaike information criterion (Akaike, 1973), minimum description length (Barron et al., 1998), and minimum message length (Wallace and Dowe, 1999)]. In our work, we choose a standard approach based on BIC (Eq. 3.4).

$$S_{BIC} = -2L + n_p \log N \tag{3.4}$$

with $L = \sum_{j=1}^N \log(p(\zeta_j | \theta))$, the log-likelihood for the considered model θ ; $n_p = (K-1) + K(D + \frac{1}{2}D(D+1))$, the number of free parameters required for a mixture of K components with full covariance matrix. Considering (1) H , the number of subjects involved in the study; (2) n , the number of trials per subject used to train the system, (3) T , the number of repetitions of each trial, and (4) $N = nT(H-1)$, the total number of data samples. The number of subjects is decreased by 1, since the model is trained on $H-1$ subjects and then tested on

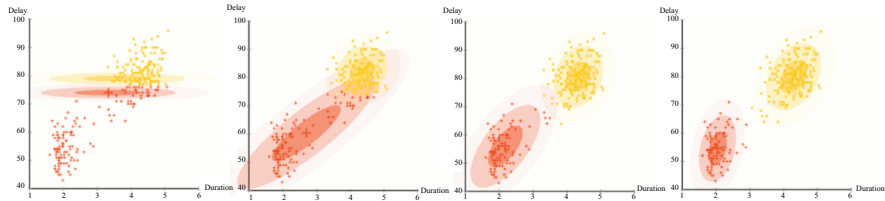


FIGURE 3.1 Example of the EM algorithm. The red and yellow ovals show how the algorithm adapts the parameters to fit the data (the red and yellow crosses).

the excluded subject h . Then a single set of data ζ_j , $1 \leq j \leq N$ in input at the framework can be written like in Eq. (3.5).

$$\begin{aligned}\zeta_j &= \{\xi(t), \alpha(t)\} \in \mathbb{R}^D \\ \xi(t) &= \{\xi_c(t)\}_{c=1}^C \\ \alpha(t) &= \{\alpha_g(t)\}_{g=1}^G\end{aligned}\tag{3.5}$$

where $C = |\xi|$, number of channels considered; $\xi(t) \in \mathbb{R}^C$, the set of values assumed from all the considered channels at the time instant t , with $\xi_c(t) \in \mathbb{R}$, the value assumed from the c -th channel at the time instant t ; $G = |\alpha|$, number of joint bending angles; $\alpha(t) \in \mathbb{R}^G$, the set of values assumed from the considered joint bending angles at the time instant t , with $\alpha_g(t) \in \mathbb{R}$, the value assumed from g -th joint bending angle at the time instant t ; and $D = C + G$, the dimensionality of the problem. The final resulting probability density function is computed as:

$$p(\zeta_j) = \sum_{k=1}^K \pi_k N(\zeta_j; \mu_k; \Sigma_k)\tag{3.6}$$

with π_k prior probabilities; $N(\zeta_j; \mu_k; \Sigma_k)$ Gaussian distribution; μ_k mean vector of the k -th distribution; Σ_k covariance matrix of the k -th distribution, K number of Gaussian components.

3.2.3 Incremental Gaussian mixture model

The construction of the probabilistic model is a time-consuming task. Furthermore, often we are not interested in the building of a new model from scratch. On the contrary, in some cases we want to update the model, adding the information from new demonstrations, in order to make the model fit better on a specific task, without losing the knowledge, the robustness, and the generality acquired from previous examples. For these reasons, we implemented an incremental version of the GMM, namely the incremental GMM, able to update the model as new demonstrations are received from operators. We implemented and tested the *generative method* described in Calinon and Billard (2007a).

The first step consists of building a GMM with the classic EM algorithm as described in Section 3.2.2. When new data are available, ξ_i , they undergo the following passages:

1. Synthetic data are stochastically generated by performing a regression on the current GMM. The generated data are a compact representation of the previous data distribution.
2. A new GMM is computed on the whole set composed of new data ξ_i and the stochastically generated ones.
3. A learning rate $\alpha \in [0, 1]$ is introduced to modulate the contribution from the new data and the stochastically generated ones. $\alpha = \frac{\tilde{N}}{\tilde{N} + N}$, with $\tilde{N}$ number of new data points available, and N number of data points from previous demonstrations.

4. Given $n = n_1 + n_2$ number of samples for the iterative learning procedure, with $n_1 \in \mathbb{N}$ number of trials from the new observations, and $n_2 \in \mathbb{N}$ number of trials generated from the previous model. The new training set is then defined by:

$$\xi_{i,j} = \tilde{\xi}_j, \text{ if } 1 < i \leq n_i$$

$$\xi_{i,j} = N(\hat{\mu}_j, \hat{\Sigma}_j), \text{ if } n_i < i \leq n$$

$$\forall_j \in \{1, \dots, Ta\}, \text{ with } T \text{ number of timestamps, with } n_1 = [n\alpha] \text{ (}.[.] \text{ nearest integer function).}$$
5. The training set of n trials is used to refine the model by updating the current set of parameters (π_k, μ_k, Σ_k) by using the EM algorithm.

3.2.4 Gaussian mixture regression

The regression process has the goal of continuously estimating the robot joints bending angles. The Gaussian mixture regression (GMR) provides a smooth generalized version of the signal starting from the GMM. GMR estimates the joint angles $\hat{\alpha}$ and their covariance from the electromyography (EMG) ξ (and eventually accelerometers φ) signals known a priori, respectively, using Eqs. (3.7 and 3.8).

$$\hat{\alpha} = E[\alpha | \varepsilon, \varphi] = \sum_{k=1}^K \beta_k \hat{\alpha}_k \quad (3.7)$$

$$\hat{\Sigma}_s = \text{Cov}[\alpha | \varepsilon, \varphi] = \sum_{k=1}^K \beta_k^2 \hat{\Sigma}_{\alpha,k} \quad (3.8)$$

with $\beta_k = \frac{\pi_k N(\xi, \varphi | \mu_{p,k}, \Sigma_{p,k})}{\sum_{j=1}^K N(\xi, \varphi | \mu_{p,j}, \Sigma_{p,j})}$, the weight of the k -th Gaussian component through the mixture; $\hat{\alpha}_k = E[\alpha_k | \xi, \varphi] = \mu_{\alpha,k} + \Sigma_{\alpha p,k} \Sigma_{p,k}^{-1} \{ \{ \xi, \varphi \} - \mu_{p,k} \}$, the conditional expectation of α_k given $\{ \xi, \varphi \}$; $\hat{\Sigma}_{\alpha,k} = \text{Cov}[\alpha_k | \xi, \varphi] = \Sigma_{\alpha,k} + \Sigma_{\alpha p,k} (\Sigma_{p,k})^{-1} \Sigma_{p \alpha,k}$, the conditional covariance of α_k given $\{ \xi, \varphi \}$.

Assuming that the parameters (π_k, μ_k, Σ_k) defining the k -th Gaussian component are decomposed as follows:

$$\mu_k = \left\{ \mu_{p,k} \mu_{\alpha,k} \right\} \Sigma \begin{bmatrix} \Sigma_{p,k} & \Sigma_{p \alpha,k} \\ \Sigma_{\alpha p,k} & \Sigma_{\alpha,k} \end{bmatrix} \quad (3.9)$$

in which the mean and the covariance of the known a priori information $P = \{ \xi, \varphi \}$ have been represented, respectively, with μ_p and Σ_p . Thus, the model is completely defined by the Gaussian components composed solely by weights, means, and covariances obtained by means of the EM algorithm. Subsequently, the information composing the model allows us to calculate a generalized motion $\hat{\zeta} = \{ \xi, \varphi, \hat{\alpha} \}$ (Fig. 3.2).

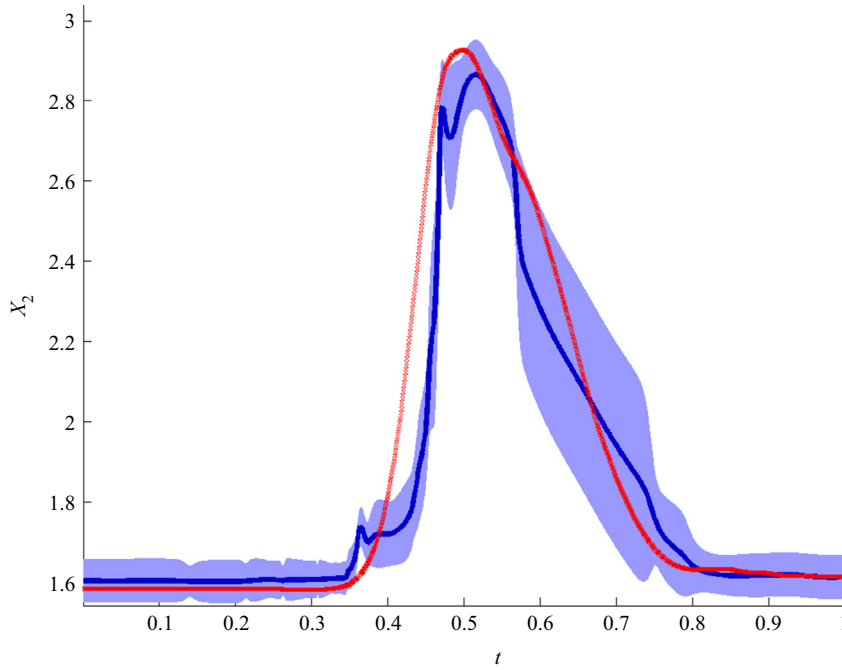


FIGURE 3.2 GMR estimation and variance (*blue*) versus actual motion.

3.2.5 System effectiveness

Besides the specific metrics established for each case study, a measure widely used for evaluating the goodness of the predicted measure (Orabona et al., 2009; Tommasi et al., 2013) is the correlation coefficient $\rho_{\alpha, \hat{\alpha}}$. This value is calculated between the predicted output $\hat{\alpha}$ and the real one α (Eq. 3.10), and it gives a measure of the model performances by means of the statistical relationships between different signals and different subjects. In particular, the correlation coefficient is a measure of the degree of linear dependence between two variables, and it is based on the covariance $[\text{Cov}(\alpha, \hat{\alpha})]$ and the standard deviations (σ_{α} and $\sigma_{\hat{\alpha}}$) of the considered variables. The resulting formula is reported in Eq. (3.10).

$$\rho_{\alpha, \hat{\alpha}} = \frac{\text{Cov}(\alpha, \hat{\alpha})}{\sigma_{\alpha} \sigma_{\hat{\alpha}}} \quad (3.10)$$

The correlation coefficient can assume all the values between 1 and -1 , where 1 is total positive correlation and indicates a perfect direct linear relationship (correlation), 0 is no correlation, and -1 is total negative correlation, or a perfect decreasing linear relationship (anticorrelation). The closer the coefficient is to either -1 or 1, the stronger is the correlation between the variables, while

the closer it is to 0, the weaker is the correlation. When the correlation reaches zero the variables are independent.

Another common measure of the effectiveness of GMM-based systems is normalized mean square error (NMSE). This function measures the goodness of fit between test and reference data. NMSE (Eq. 3.11) costs vary between $-\infty$ (bad fit) to 1 (perfect fit).

$$\text{NMSE}(t) = 1 - \left\| \frac{\hat{\alpha}(t) - \alpha(t)}{\hat{\alpha}(t) - \mu_t(\alpha)} \right\|^2 \quad (3.11)$$

where t is the temporal instant from the beginning of the trial; $\hat{\alpha}(t)$ is the estimated output at the instant t ; $\alpha(t)$ is the groundtruth at instant t ; $\mu_t(\alpha)$ is the mean along the time of considered quantity. In this work, we used both methods as an initial feedback for understanding if a model could work or not in an actual test with the robot.

3.3 Automatic assembly

The main objective in this industrial case is to perform the automatic assembly of a car door with its module. The evaluation of the developed techniques has been carried out in a dedicated facility for Industry 4.0 in Stuttgart with the constraints imposed by real industrial cases to guarantee success and repeatability of the tasks in a quantifiable way. The set of sensors available in the facility was predetermined without the possibility of adding new sensors or modifying the already existent ones. We had to work with a previously installed system as a part of a factory supply chain that was partially obsolete and outdated. Industrial settings were composed of complex and challenging workcell layouts with changing illumination and tight workplaces. Moreover, it was a dynamic environment with people working alongside robots in a collaborative manner and uncertain position of parts to be assembled. Starting with the Robot Programming by Demonstration paradigm, we designed a framework to learn novel robot trajectories and configurations on the fly from human demonstrations.

Such an approach is quite novel in research, and few attempts are described in the literature. As suggested by [Chen and Liu \(2013\)](#), flexible assembly applications are uncommon and only a small portion of industrial robots are used to perform tasks with variability in the parts. In fact, conventional industrial robots are not able to adapt to changes in the assembly processes. On the other hand, [Goyal et al. \(2012\)](#) indicated flexibility in automotive manufacturing as one of the more competitive weapons in the economical analysis of the North American automotive industry. They proposed the possibility of switching easily and with a lower risk from one production line to another as a main advantage in future achievements with respect to foreign competitors. The reduced risk should permit industries to

invest in low-volume high-risk products, since the money and time lost would be minor and the production line would remain the same.

While the hardware and firmware composing the robotic system were fixed, we had the possibility to use the Robot Operating System (ROS) as the programming tool. ROS is now the standard de facto research robotic framework, but it has been only recently accepted as a tool for industry. The importance of ROS has been expressed in [Tavares and Sousa \(2015\)](#). They analyzed a pick-and-place task by combining several layers of control. Using ROS in developing industrial applications gives the possibility of efficiently dividing layers into standardized and compact blocks able to interact with each other to autonomously correct errors during the accomplishment of a task. In our solution, we took advantage of the modularity and standardization of ROS characteristics to fuse together visual and robot learning techniques in order to face the variability in the system configuration. The stability and reliability of each method have to be enhanced to meet the requirements in terms of elapsed time and hardware compatibility.

The human–robot interface has been designed to easily teach the system with novel door assembly combinations by starting with previous works. [Vakanski et al., 2010](#) suggested taking advantage of the robots' ability to learn from their surroundings, transferring skills to the robot thanks to multiple demonstrations of the same skill under similar conditions. Vakanski's idea was to learn the robot trajectory by observing a subject moving a tool. Instead, in our solution, the person actually moves the robot to acquire information about the desired motion. The robot has to infer a generalized trajectory obtained by extracting relevant features from the demonstrations.

3.3.1 Task and system description

The following paragraphs introduce the setup of the cell and the objectives to achieve the correct automatic assembly of a car door with its module. The module and the door are represented in [Fig. 3.3](#). The positions of the door and module could vary by a few centimeters in translation and a few degrees in rotation in each direction. The testbed is composed of three tasks:

1. Pick and insert door module: in the pick phase we have to locate the door module using visual and force information, pick it up, and reach a reference position. Then the robot has to place the module into the door, and come back to the reference position without detaching it.
2. Screw door module: this consists of detecting, picking up, and inserting three screws into three relevant holes to fix the module onto the door.
3. Teach and assemble unknown door: the whole assembly has to work for a novel pair of module and door.

The hardware available at the facility in Stuttgart consisted of a lightweight collaborative robot (Universal Robots UR10) equipped with three sensors: a 3D

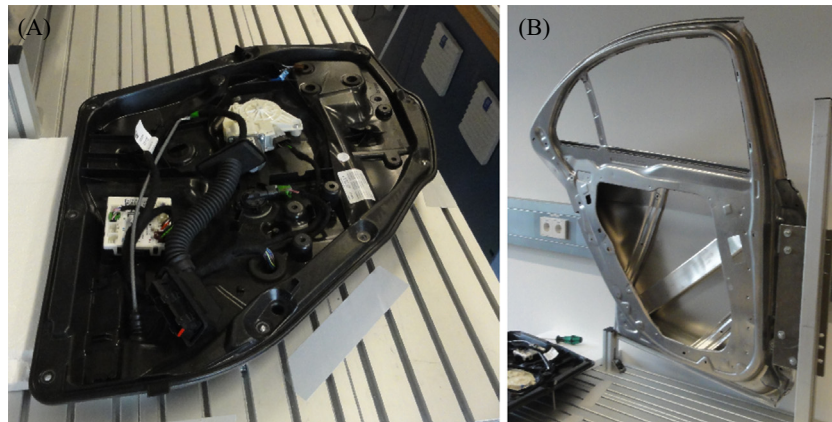


FIGURE 3.3 (A) Plastic module, (B) car door where the module has to be inserted.

sensor camera (PMD CamBoard Nano), a stereo camera (VRMagic D3), and a 6D force-torque sensor (Robotiq FT150). A vacuum gripper, composed of six suction cups, and a screwing tool (Weber Pluto 6D) were available and could be automatically attached or detached from the robot flange using a tool-changing rack (Schunk SWS011). We replicated the setting in our laboratory, using as a basis the same lightweight collaborative robot, the Universal Robots UR10, but equipping it with different sensors. A PMD CamBoard Pico was used as a 3D camera, a pair of Philips SPZ5000 webcams were calibrated to work as a stereo camera, while no force sensor was mounted on the robot. A vacuum gripper and a screwing tool were built by means of 3D printed materials to mimic the functionality available in the original system. The tools could be manually changed from one to another. A central working station connected through Gigabit Ethernet collected data coming from the sensors and going to the controllers. ROS was used as the framework to enable interaction with the system. Topics, services, and actions coming from the system, as well as device drivers, were established in advance to be able to use them in both settings. Positions and orientations of every relevant frame were published and updated using the ROS TF package. A rough virtual model of the environment was also available and objects were coherently placed in the scene depending on the published positions. 2D and 3D cameras were provided with a default intrinsic and extrinsic calibration.

3.3.2 Methodology

The proposed tasks are connected to three main constraints: (1) limited time available for developing the solution, (2) flexibility needed to deal with position tolerances and unknown modules and doors, and (3) usability and reliability of

the teaching procedure. These characteristics led us to propose a solution able to face both known and unknown door assemblies in a very similar manner. In fact, different modules and doors rely on similar structures, and these features can be used as input for the framework. We wanted to extract these common characteristics to simplify and speed up the new module and door identification. In order to successfully solve the previously described tasks we used the following pipeline: (1) learn the relative positions of each screw hole in both module and door; (2) learn the gripping and inserting trajectories through human demonstrations; (3) identify both module and door real positions by visual inspection; (4) pick and place of the module by transposing the learned motion to real position; (5) identify screw positions; and (6) screwing.

In the learning phase, we collected template images for each part to identify. The idea was to extract relevant visual information in order to recognize them during the part inspection in order to build a coarse virtual model of the environment. A combination of robot learning from kinesthetic demonstration and inverse kinematics was used to learn how to pick and place the module. The variability and robustness of the system were granted by collecting several repetitions of the same action, performed by different subjects. A visual system was used also for finding the screws and pick them up and fixing the module. A template matching approach was used for the screwing operation. Again, a door inspection was performed to look for screw hole positions. Once a match was identified, the system aligned the screw with the hole using the previously acquired template in order to perform the insertion.

3.3.2.1 Learning phase

The learning phase mainly involved how to correctly pick the module and insert it in the door. These operations could be very easy or critical depending on the context and the complexity of the parts to be assembled. The module was composed of several elements including some flexible cables possibly assuming different configurations while the task evolved. The gripper provided for performing the picking action had a fixed base, while suction cups attached on its extremities were able to change position slightly. Positioning the gripper in a consistent manner obtained a robust layout which was essential to assure a safe pick. This operation has to be performed in advance, since the surface of the module varies a lot and it is not always smooth. Moreover, the module is quite heavy while the suction cups do not have great gripping power in the case of unbalanced loads. Selecting the wrong gripping position can result in a loss of the vacuum system and the module falling due to a displacement in weight or position of the suction cups. Once the module is properly picked, it has to be placed into the door. A series of coupling pins should be inserted into slots in the door to hold up the module, while avoiding cables that may obstruct the movement. The motion should be executed precisely by placing the cables, and proceeding diagonally to insert the first coupling pin. Finally, the module should be straightened, and the rest of the pins set into place. Pinching the cable or failing to place a coupling

pin led to incorrect insertion and consequential falling of the module. Obviously, the placing trajectory is really dependent from the initial gripping position. Therefore a successful picking does not correspond necessarily to good performance in placing the module.

The described constraints could be easily met when the task is performed by a human being. Indeed, people have the capabilities to understand the task, test the selected strategy in a few trials, and move the robot accordingly to fulfill the objectives. Nevertheless, recording a single execution is not enough to achieve a smooth generalized trajectory able to take into account the intrinsic variability in the tasks. In order to obtain such motion, we used a Robot Learning by Demonstration paradigm able to build a robust model of the movement starting with a series of demonstrations. In particular, we recorded data directly from the robot while the subject was free to physically guide the manipulator following the desired path (Fig. 3.4). In this way, it is possible to let the robot learn a novel task in a short time and without the need for additional staff for robot programming.

In order to avoid unnecessary variability in the motion and reduce the number of examples we decided to keep human demonstrations as short as possible. Short trajectories are computed quicker, resulting in a more standardized movement, while allowing a simpler and consequently safer robot activity. We mixed together probabilistic robot learning with inverse kinematics to take advantage of both systems. The robot reaches fixed and safe positions close to the targets by using an inverse kinematics engine obtaining better performances in both reliability and time. The final part of the movement, namely the most complex one, is performed by using inferred trajectories computed through robot learning. Ten repetitions of the movement performed by different subjects were recorded from an arbitrary selected initial position. The angles assumed by each joint while the robot is manually controlled have been considered for building the probabilistic model. Since the door and module positions are not known a priori, visual feedback is used to compute the actual configuration of the system before proceeding with the real picking and placing motions.

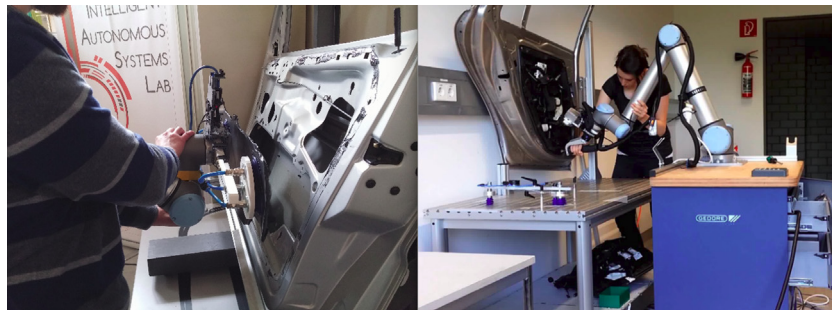


FIGURE 3.4 The robot is physically guided to learn the motion through kinesthetic teaching.

The raw data recorded from robot encoders have to be preprocessed in order to be able to generate a good probabilistic model. As a first step, they are filtered to remove artifacts, such as periods in which all the joints were still. Doing so all the data not correlated with the movement are eliminated, maintaining exclusively motion information. This process led to more robust and smooth trajectories while speeding up the creation of the model. Once the model was built, the final motion was estimated thanks to a regression technique.

Starting from GMM as accurately described in Section 3.2 and having n as the number of repetitions of the task, and T the number of observations acquired during each trial, the total number of data samples is $N = nT$. A single data input at the framework ζ_j , $1 \leq j \leq N$ is described in Eq. (3.12).

$$\begin{aligned}\zeta_j &= \{t, \alpha(t)\} \in \mathbb{R}^D \\ \alpha_x(t) &= \{\alpha_g(t)\}_{g=1}^G\end{aligned}\tag{3.12}$$

with G , number of joint bending angles; $\alpha(t) \in \mathbb{R}$, the value assumed from g -th joint bending angle at the time instant t ; $\alpha(t) \in \mathbb{R}$, the set of values assumed from the considered joint bending angles at the time instant t ; $D = G + 1$, the dimensionality of the problem. The resulting probability density function is computed as shown in Eq. (3.6). The GMR provided a smooth generalized version of every joint angle starting from the GMM (Fig. 3.5). Every joint angle $\hat{\alpha}$ and its covariance are estimated from the known a priori time instant t , respectively, using Eqs. (3.13 and 3.14).

$$\hat{\alpha} = E[\alpha | t] = \sum_{k=1}^K \beta_k \hat{\alpha}_k \tag{3.13}$$

$$\hat{\Sigma}_s = \text{Cov}[\alpha | t] = \sum_{k=1}^K \beta_k^2 \hat{\Sigma}_{\alpha,k} \tag{3.14}$$

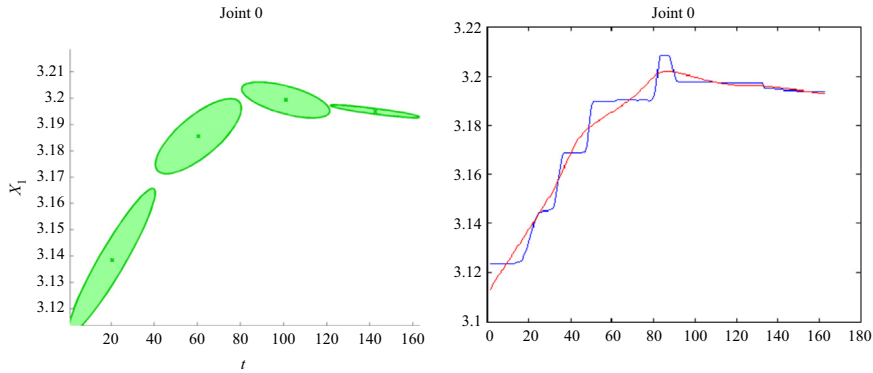


FIGURE 3.5 Modelization of Joint 0 with GMM and continuous estimation of Joint 0 angle retrieved with GMR.

with β_k , the weight of the k -th Gaussian component through the mixture, $\hat{\alpha}_k$, the conditional expectation of α_k given t , $\hat{\Sigma}_{\alpha,k}$, the conditional covariance of α_k given t . The parameters (π_k, μ_k, Σ_k) defining the k -th Gaussian component are decomposed as shown in Eq. (3.9). The described framework could be used with known settings as well as with novel unknown door–module pairs. It gives good results both in time needed to teach the tasks and in robustness in reaching the goals. Nevertheless, it is hugely dependent on the information provided by the visual counterpart system.

3.3.2.2 Module and door identification

As earlier, we tried to adopt the same base procedure for both known and unknown objects. We decided to implement a reliable and adaptive identification system working for both door and module. A stereo camera was used to obtain a visual servoing procedure able to align the robot with respect to an object. A simple image-based visual servoing is very difficult to implement due to a lack of a common robust set of visual features to use. On other hand, a position-based visual servoing (PBVS) approach supposes to know a priori a model of the object, not provided in this challenge.

However, our algorithm compensates for this lack with the 3D knowledge coming from the stereo camera. The approach is composed by a training phase and an iterative query phase. In the training phase, the robot is placed into a known position $^w\xi_{cd}$, where both cameras could see the same region of interest inside the object. A stereo pair template is acquired and a keypoints extraction is performed using a *FAST* algorithm (Rosten and Drummond, 2005, 2006) for the detection and *ORB* (Rublee et al., 2011) as descriptors. A sparse triangulation is computed after a keypoints matching between left and right templates using intrinsic and extrinsic camera parameters. In this way, a model representing the object is obtained from this set of 3D points. Finally, the object pose with respect to the camera frame $^{cd}\xi_o$ is estimated with a *virtual visual servoing* algorithm (Marchand and Chaumette, 2002) based on the 3D information of the object.

In the query phase, we used a single-camera approach. For each iteration, a template matching with the desired template was performed in order to identify a valid area where extracting keypoints on the current frame (Fig. 3.6).

Then, we matched current and corresponding keypoints by using the available 3D coordinates in the trained model in order to obtain the current camera pose with respect to the object $^c\xi_o$. The displacement between the current and desired positions could be easily computed as described in Eq. (3.15).

$$^c\xi_{cd} = ^c\xi_o * ^o\xi_{cd} = ^c\xi_o * ^{cd}\xi_o^{-1} \quad (3.15)$$

After the robot movement the effective displacement could be different due to noise presence (Eq. 3.16).

$$^c\hat{\xi}_{cd} = ^c\xi_{cd} + \Delta\xi \quad (3.16)$$

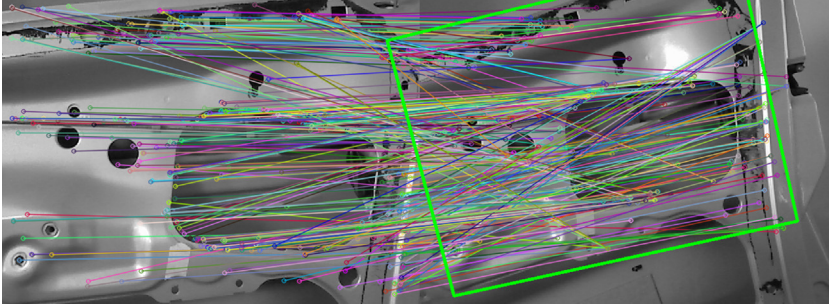


FIGURE 3.6 Keypoints extraction for the current frame with respect to the desired template.

The procedure was iterated to satisfy the condition in Eq. (3.17).

$$\Delta\xi \leq \Delta\xi_{\max} \quad (3.17)$$

where $\Delta\xi_{\max}$ is related to the desired accuracy. A simple template matching in 2D was used to find the screw and hole positions to perform the screwing task.

3.3.3 Results

GMM has been used as a probabilistic model to predict angles of $G = 6$ robot joints. Good results can be achieved with $k = 10$ Gaussian components. Using too few Gaussian components causes the generation of a too general model that is unable to handle the variability of the signal. In contrast, if k is large the final model will be too complex. Experimentally, for module and door identification, an average of six iterations were needed to reach a precision of 1 mm for translation and 0.2 degrees for rotation. The training phase allowed us to perform a PBVS task in an easy way, without any actual model of the object or a priori information. Therefore the identification process for unknown objects becomes quite simple and immediate. In fact, the operations needed to perform the tasks were restricted to (1) updating the templates collected for the stereo camera pairs, and (2) recomputing ${}^{cd}\xi_o$ through keypoints matching and triangulation. The query phase remained unchanged. We were able to correctly pick and place the module and the framework is robust to module shifts Fig. 3.7.

3.4 Manufacturing of electric motors

This task aims to increase the competitiveness in European electric vehicles and motors manufacturing. Automation is already applied at different levels in this field, nevertheless it is facing strong competition from countries with low labor costs. The interest in electric motors has increased in recent years, to reduce the



FIGURE 3.7 The robot was able to insert the plastic module into the door, both in Stuttgart and the laboratory facility.

use of fossil fuels for environmental reasons, with the ideal goal of eliminating nonrenewable energy resources in a few decades. Increasing process efficiency would strengthen a very critical sector for Europe, as it is expected to reach \$22.32 billion by 2022, registering a CAGR of 3.7% during the forecast period 2016–2022 (Pal, 2016).

Our aim is to reduce costs and increase flexibility with the following contributions: (1) important reduction of setup time and costs of the winding machine, thanks to the simplicity and flexibility of the proposed approach; (2) increase in the quality of the final motors, thanks to the increased amount of copper that the robot will be able to insert in each coil with respect to manual winding; (3) possibility to parallelize the winding operations, dramatically increasing the production rate; (4) decreased number of defected cores, thanks to an advanced quality inspection system; and (5) reduction of environmental impact of the production process, thanks to a reduction of wasted copper wire.

An automatic system for coil winding has to be affordable to a wide range of users: from small-medium enterprises (SMEs), producing small batches of motors and frequently changing product design, to large companies, having a market request of several thousand standard units. The low flexibility of automated winding machines (Feldmann et al., 2006), that is, the time and costs required to switch from one design to another, coupled to their high cost (up to 100,000 Euros), force small manufacturers (especially SMEs) to employ human operators in this task. The handcrafted job is obviously much more flexible, but more expensive (because of labor cost and equipment), and for the worker it can be distressing, frustrating, and repetitive. Few attempts at use of a robotic cell for coil winding have been made (Feldmann et al., 2006). We aim to achieve the product flexibility required for this business sector by developing an interactive robotic cell for this task. Such a reconfigurable cell has been provided with learning capabilities. The cell is suitable for winding the coils of several kinds of electric machines, starting from the information from a simple teaching interface that can easily be used by operators without specific skills in robotics. This goal has been gradually reached by passing through three main phases: (1) human interface, (2)

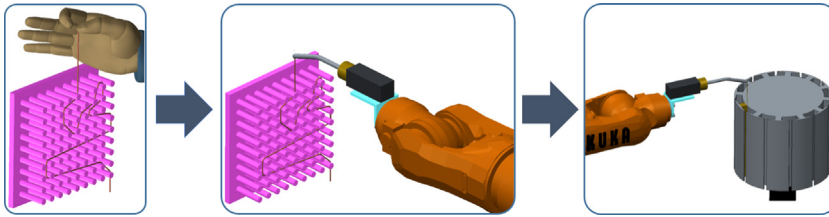


FIGURE 3.8 The three-phases approach adopted for this case study, with (1) the human interface on the left, (2) the lab scenario in the center, and (3) the industrial scenario on the right.

lab scenario, and (3) industrial scenario (Fig. 3.8). The need for an alternative power supply system for cars will be a crucial issue in the coming years. Up to now, important steps forward have been made in electrical motors. Factories like Tesla produce cars whose motor performances are comparable with traditional motors. Here, the goal is the development of an automatic tool, able to create autonomously an electric motor. There are now industrial machines able to wind up coils. These machines are very expensive and are not flexible.

The electric machine manufacturers have to deal with uncertain sales volumes, therefore the batch sizes in the manufacturing process vary. Furthermore, continuous efforts are undertaken by the industry R&D departments to develop optimized electric machines with increased efficiency, increased power density, decreased manufacturing cost, etc. This also leads to currently uncertain motor designs for the manufacturing processes. In the product lifetime its design may change several times. Also, there is a trend in the manufacturing industry to work with minimum or even zero stock; the products being manufactured after receiving the orders. The development of flexible production technologies that can be adapted to varying motor constructions is an existing concern as long as manufacturing uncertainties remain. The process related to coil manufacturing and their transfer/insertion into the stator are addressed.

The concept of flexible production will use a needle winding technique. The production process is divided into coil manufacturing and insertion of these onto the stator. The coils are wound on frames, after which they are mounted onto the stator. For this particular application the winding process is restricted to concentrated windings. However, distributed windings or even complex winding schemes are achievable by winding individual coils. The proposed production process will have the potential to allow three-dimensional shapes of the coils and complex winding schemes. Thanks to its flexibility, the process can easily adapt to newly developed motors, without the need for expensive and time-consuming changes in the layout. Particularly, the removal of auxiliary special wire guides implies a reduction of the setup times of the winding machine by 50%. The robotic-based system does not require any machining of new fittings for every new production batch. This will lead to an additional reduction of setup costs by 70%, mainly in terms of effort.

During the project, we faced the following challenges: (1) teach the robot how to properly wind the coils of stator/rotors; (2) robotize the manufacturing process of electric machines, in particular the winding of coils on stator or rotor cores; (3) detect and report noncompliances in the process of the coil winding. The selected electric motors have the following features: (1) frameless torque motors designed to be compact, high performance, and cost effective; (2) allow direct coupling with the payload, eliminating parts of mechanical transmission; (3) maintenance free; (4) high-energy NdFeB magnets maximize torque density. The main applications for the proposed motors are electric vehicles, machine tools, laser scanning and printing, motion simulators, rotary stage, robots, and tracking systems.

3.4.1 Task and system description

The case study has been divided into three phases.

3.4.1.1 Human–robot interface

The first phase is focused on developing a solid learning system and a reliable human–robot interface. Indeed, the objectives of this phase were agreed in order to create the basis for the following phases. The approach will be used during tests in lab and industrial scenarios to finally wind up the stator coils of an electric machine. In this phase, the robot has to learn an arbitrary path. The operator teaches the selected path by moving a tool in a natural manner to deploy the wire through a pin table, for a relatively low number of demonstrations. The user guides the copper wire through the pole grid using a tool designed ad hoc to maintain the wire constantly stretched, and prevent the possibility of knotting. The system records the covered trajectories using a camera network composed by both 2D and 3D cameras. The camera network system has also the capability to monitor the workspace by detecting and tracking humans for safety and collaboration purposes. The idea is to have the robot stop as soon as a human is detected in a danger zone around the machine by the cameras. In order to demonstrate the consistency of the approach used, the system has to analyze a trajectory decided by a person not knowing the system. To select a pole to pass through, the operator has to roll up the wire twice around each choice.

3.4.1.2 Lab scenario

In the lab scenario (Fig. 3.9), the key robot action is the winding motion around a fixed point as an initial step toward the final goal of winding the coil of a real electric motor. Previous expertise in learning systems has been exploited to teach the robot how to unroll a wire following a specific path in order to pass a wire through a peg grid composed of different possible routes, as shown by the operator. A 6 degrees of freedom (DoF) robot manipulator, equipped with the same custom wire deployment system used by the human, has to replicate the motion of the operator and unroll a wire along the path taught in the previous phase. The result is considered correct if the robot is able to replicate the pole sequence in

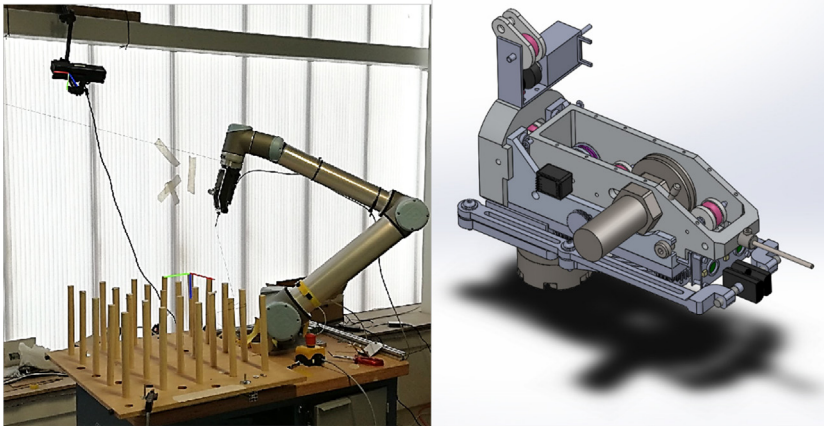


FIGURE 3.9 System setup for the lab scenario.

the exact same order selected by the operator. Both the operator and the robot start from a fixed position. Moreover, the tool has to maintain the tension of the wire, while allowing the user to detach the tool for demonstrating the task and to attach it back on the robot when finished. No sensor is integrated in the end effector, as the only aim of the robot is to copy the operator motion. As the robot deploys the wire, particular attention has to be kept in order to prevent the wire from becoming stuck or breaking. To do so, it is important that the robot performs a human-like movement, choosing a smart way for moving from one pole to another, avoiding useless changes of direction or turnabouts. These observations have been considered while developing the learning by demonstration framework since they are fundamental in the following phase.

3.4.1.3 Industrial scenario

In the industrial scenario, the objective is to plan the path for winding a coil to be mounted on a real stator composed of an electric motor. The system takes into account the coil dimensions (height, width, and depth), the number of turns in the coil, the wire thickness, and allowed tension. The planning is based on a learning framework previously developed in [Michieletto et al. \(2013\)](#) and [Tosello et al. \(2014\)](#) to improve the system developed in the previous phase to compute the trajectory to be covered by the robot tool and explained in depth in [Stival et al. \(2017\)](#) and [Castelli et al. \(2017\)](#). The learning system has been trained with several examples generated using an initial set of human demonstrations, with the idea of improving the internal model in an iterative manner and increasing the performances of the whole winding procedure. Of course, it is still possible to refine the computed trajectory by teaching the robot a better route through human demonstration. The idea is to enable the system to wind up a coil to be mounted on a stator that has never been seen before. The parameters of pole dimensions,

number of turns in the coil, wire thickness, and desired tension are provided as input to the robot by the operator, without the need for specific sensors to identify them. Based on the given information, the system chooses the proper coil from a coil hub and the robot tool gripper picks and places it on the adjustable winding stage. Later, the tool clamps its wire to the winding stage and starts winding the coil. A set of basic quality inspection protocols, based on number of turns, wire tension, and wire round distribution unity have been introduced, in order to guarantee a high standard of the winding process. A tension sensor has been integrated into the robot end effector in order to control the wire tension. The output of the sensor has been used to close the loop in the controller, adjusting the joint trajectories to match the desired output. This feature allows the robot to keep the wire tension as much as possible within the prescribed range, in order to avoid picks in the tension and to reach optimal performances of the wound coil. Finally, the robot gripper picks the wound coil and places it on the empty stator slot. The process is summarized in Fig. 3.10. The robot working process has to be able to adapt to different sizes of poles and input parameters to control the winding process. The system does not need human intervention in wire handling, online quality control, picking, and placing. In fact, the robotic platform has been provided with automatic wire clamping and cutting, sensors for determining wire tension and wire rounds position, and a custom gripper for coil picking and placing from the hub to the winding stage and from the winding stage to the stator.

We worked on five different types of electric motors in order to design and optimize a flexible production of the coil winding procedure. A stator consists of a laminated steel core in whose slots is located a three-phase star-connected winding. A rotor consists of a magnetic steel ring on which are placed high-energy permanent

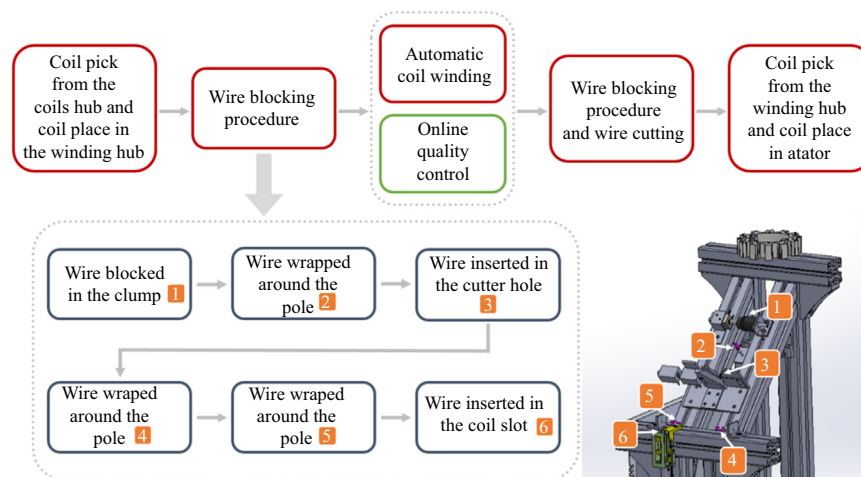
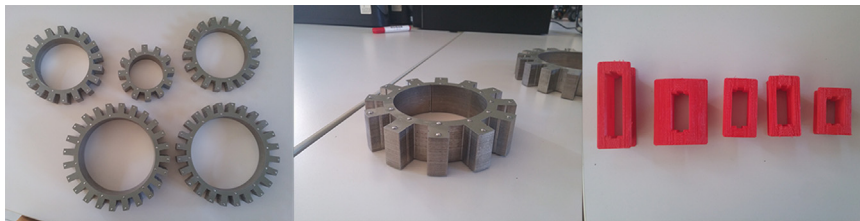


FIGURE 3.10 Sequence of automated winding procedure.

Table 3.1 Specifications of the motors produced by the manufacturer during the project.

Parameters	Unit	M1	M2	M3	M4	M5
External diameter	mm	128	178	178	252	252
Inner diameter	mm	80	120	120	160	160
Actual length	mm	30	20	30	30	50
Rated power	W	1600	2400	3100	3000	4500
Conn. torque	N m	13	24	30	36	54
Peak torque	N m	30	53	69	82	124
Rated speed	rpm	1200	1000	1000	800	800
No load speed	rpm	1500	1350	1200	900	850
Inertia	Kg m ²	0.09	0.03	0.032	0.055	0.06
Weight	Kg	3.7	5.65	6.65	8.5	10
Phase conn.		Y	Y	Y	Y	Y
Number of poles		14	20	20	20	20

**FIGURE 3.11** Stators and coils composing the motors used in the project.

magnets. Applications for the proposed motors include electric vehicles, machine tools, laser scanning and printing, motion simulators, rotary stage, robots, and tracking systems. The specifications of the proposed outer rotor frameless motors are reported in [Table 3.1](#), while [Fig. 3.11](#) shows some of the components used in this scenario.

The system takes into account the coil dimensions (height, width, and depth), the number of turns in the coil, the wire thickness, and allowed tension. These characteristics improve the system capabilities to compute the trajectory to be covered by the robot tool. In fact, the considered features are used to plan the path for winding a coil never seen before by the system. Of course, it will still be possible to refine the computed trajectory by teaching a better route through human demonstration. Novel demonstrations can be acquired by the learning system to iteratively improve its internal model and increase the performances of the whole winding procedure. The parameters of pole dimensions, number of turns in the coil, wire thickness, and desired tension are provided as input to the robot by the operator, without the need

for specific sensors to identify them. Based on the given information, the system chooses the proper coil from the coil's hub and the robot tool gripper picks and places it on the adjustable winding stage. Later, the tool clamps its wire to the winding stage and starts winding the coil. A set of basic quality inspection protocols, based on the turns count, wire tension, and wire round distribution unity have been introduced, in order to guarantee a high standard of the winding process. A tension sensor has been integrated into the robot end effector in order to control the wire tension. The output of the sensor will be used to close the loop in the controller, adjusting the joint trajectories to match the desired output. This feature allows the robot to keep the wire tension as much as possible within the prescribed range, in order to reach optimal performances of the wound coil. Finally, the robot gripper picks the wound coil and places it on the empty stator slot.

3.4.2 Methodology

In our solution, we made robot learning and inverse kinematics work together in order to accomplish a more general and robust solution. The basic idea is to take advantage of the human capability to find a solution by simply looking at the problems, while leaving the robotic system to handle the mathematical computations. For example, it is very easy for people to find the path to pass through a series of poles, while it is very difficult (or even useless) for them to compute the robot joint positions to guide the robot end effector along the same trajectory without interfering with the copper wire. Therefore the set of useful information extracted from the trajectories performed by humans has been described using a GMM (Calinon et al., 2007), while a GMR has been used for retrieving a unified smoothed trajectory for the robot TCP. The learned trajectory has been translated from Task Space, in the tracking system reference frame, into robot Joint Space by means of an inverse kinematic engine.

During this work, we considered mainly three aspects in order to make the robot correctly reproduce the operator actions. Two of them are strongly related with the human–robot interface, the latter regards robot motion for both lab and industrial scenarios. At first, we need to identify the objects in the scene and select the order of operations. Second, we detect the best entrance and exit position for wrapping the wire. Third, we have to make the robot deploy correctly the wire.

3.4.2.1 Pole selection

While the identification of the objects like coils and stators (industrial scenario) has been performed following the same approach described in Section 3.3, a different procedure has been developed for the detection of the poles selected by the operator (lab scenario). A camera network has been used to track people in the scene and compute information about the trajectory when moving the wiring tool during demonstrations (Fig. 3.12). No special marker or material was placed on the person or on the tool. An automatic tool was developed to extract useful data from videos with almost no human intervention. Starting from the trajectory

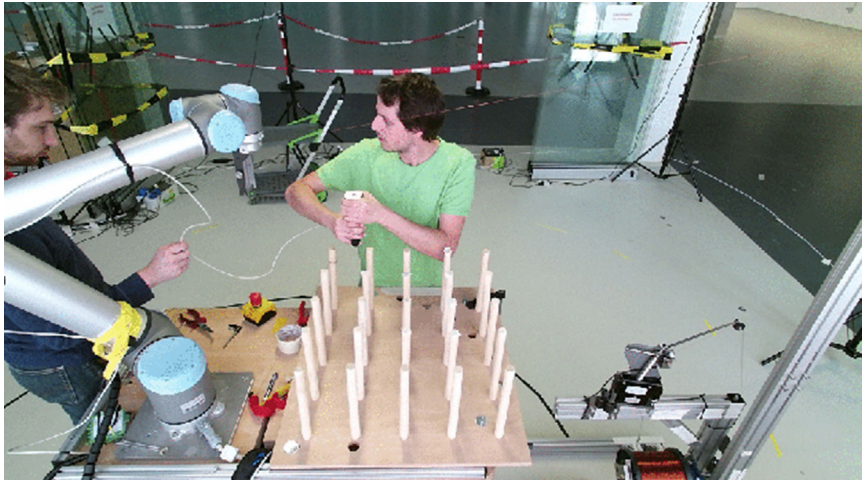


FIGURE 3.12 Human demonstration.

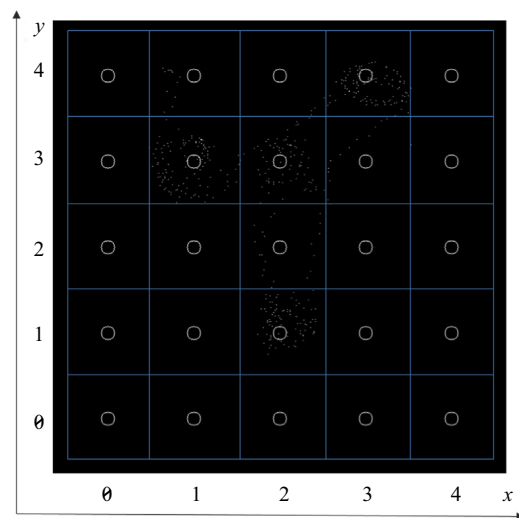


FIGURE 3.13 Trajectory grid.

extracted from the camera network system, the goal is to detect which poles the operator selected and in which order. The information was transformed and projected on the 2D plane, so the input data are a sequence of (x, y) coordinates of the tool position (Fig. 3.13). The selected approach is based on the consensus algorithm. The solution to the consensus problem is the result of the agreement among a number of processes (or agents). The result we would like to achieve is

the pole selected by a person while deploying the wire. Basically, the consensus problem requires agreement among a number of agents for a single data value. Similarly, our pole selection algorithm looks at which poles have been visited and in which order. Some of the processes could be unreliable since the visual system has estimated them wrongly, therefore our selection algorithm should be able to confirm the information coming from a single point of the trajectory by comparing it with the others. In the same way, consensus protocols verify candidate values, and agree on a single consensus value.

In our consensus algorithm, adapted for this particular case, we start dividing the grid in different areas belonging to the “nearest” pole without overlapping, so that every pole is in the center of a square. The idea is to assign to each pole an afferent area homogeneously distributed. After the grid division, we perform a sort of clustering operation, where each point is substituted with the relative pole area. Once we count the number of points belonging to each pole, a threshold helps in recognizing the selected poles, without mistakenly choosing poles where the tools passes often without selecting them. It is worth mentioning that each pole can be visited only once in a specific trajectory. Considering the visit order helps in correctly detecting the poles in the right order. A preprocessing phase is needed for removal of the still periods in which the tool is motionless in a fixed point. This case could alter the outcome, since it would result in many consecutive samples in the same pole area. The pole detection algorithm is described accurately in Fig. 3.14.

Algorithm1 Path detection

```

1:  $\leftarrow$ trajectory // sequence of (x,y) coordinates
2: visited_poles  $\leftarrow$  0
3:  $n \leftarrow$ rows(trajectory)
4:  $np \leftarrow 25$  // num poles
5: still points remotion
6: for all (x,y)  $\in$  trajectory do
7:   clustering //  $\forall (x,y) \in$  trajectory find pole  $\in [1,np] : (x,y) \in$  pole belonging area
8:   for all  $p \in [1, np]$  do
9:      $cell\_duration[p] \leftarrow \sum_{i=1}^n i \Leftrightarrow trajectory[i] == p$ 
10:     $count\_visits[p] \leftarrow \sum_{i=1}^n i \Leftrightarrow trajectory[i] == p$ 
11:     $mean\_time[p] \leftarrow cell\_duration[p] / count\_visits[p]$ 
12:     $visited\_poles \leftarrow visited\_poles + 1$ 
13:  $count \leftarrow \sum_{i=1}^{np} count\_visits[i]$ 
14:  $threshold \leftarrow floor(count / visited\_poles)$ 
15:  $fixed\_threshold \leftarrow 40$ 
16: if  $threshold > fixed\_threshold$  then
17:    $threshold = fixed\_threshold$ 
18: for all  $p \in [1, np]$  do
19:   if  $count\_visits[p] > threshold$  then
20:     ordered insertion of  $p$  in final_path based on mean_time

```

FIGURE 3.14 Pole selection algorithm.

3.4.2.2 Entrance and exit position estimation

In order to avoid breaks in the wire or tangles it is important that the robot begin and end its winding motion in the correct position, both for poles (lab scenario) and coils (industrial scenario). The correct place depends mainly on the previous position of the tool. For example, if the previously visited pole is above on the left with respect to the currently selected pole, the tool should come from the left. Similarly, if the tool is placed on the right of a coil, the approaching direction to start the winding will be also on the right. This step is crucial to understanding how to practically perform the winding. In order to do so, we exploit human knowledge and expertise. Usually, a person is capable of understanding which is the best way to reach a fixed point while also dealing with constraints. Accordingly, we can take advantage of human operator knowledge and overcome the planning limits.

Our goal is to compute the (x, y) coordinates of the start winding point and the end winding point. These coordinates are computed using a probabilistic framework. We use the start and the end winding point coordinates recorded from many winding tests performed by many different operators. Human expertise and knowledge give us the best way to overcome this critical issue in a probabilistic way. Furthermore, using many experiments performed by different subjects brings generality into the system, since each person could think of a different, although correct, solution. The use of several executions allows the achievement of a generalized solution, which takes into account the intrinsic variability in the tasks. We obtained such results by using a Robot Learning by Demonstration paradigm, able to build a robust model of the coordinates starting from a limited number of demonstrations. Another advantage to this solution is that it could be used also by unskilled operators, since no further information or training phases are needed. The interesting coordinates are selected from tool trajectory tracked during the operator motion. GMM (Calinon et al., 2007) described in Section 3.2 is used as a probabilistic framework to predict the (x, y) coordinates.

In order to build the probabilistic model we introduce two fictitious positions in the system: $pos - 1$ and $pos + \infty$. The first represents the robot's starting point, while the second represents the final goal, both far from the object to be wound. Considering data collected from S subjects, each of them completed the task T times and for each task performed P different winding operations. The total number of data samples is $N = S \times T \times (P + 1)$. A single data input at the framework ζ_j , $1 \leq j \leq N$ is described in Eq. (3.18).

$$\zeta_j = \{\alpha_w, \alpha_h, \beta_w, \beta_h, \gamma_x, \gamma_y, \lambda_x, \lambda_y\} \in \mathbb{R}^8 \quad (3.18)$$

with α_w, α_h , respectively, being the width and height of the previous position of the tool; β_w, β_h , respectively, the width and height of the object to be wound up; γ_x, γ_y , respectively, the x and y coordinates of the exit position; λ_x, λ_y , respectively, the x and y coordinates of the entrance position. The resulting probability density function is computed as in Eq. (3.6).

The GMR provides smooth and generalized exit and entry points for the considered poles starting from the GMM. Every exit and entry points and their covariance are estimated from the known visited poles using Eqs. (3.19 and 3.20):

$$\{\hat{\gamma}_x, \hat{\gamma}_y, \hat{\lambda}_x, \hat{\lambda}_y\} = E\left[\{\gamma_x, \gamma_y, \lambda_x, \lambda_y\} \mid \{\alpha_w, \alpha_h, \beta_w, \beta_h\}\right] = \sum_{k=1}^K \eta_k \{\hat{\gamma}_x, \hat{\gamma}_y, \hat{\lambda}_x, \hat{\lambda}_y\} \quad (3.19)$$

$$\hat{\Sigma}_s = \text{Cov}\left[\{\gamma_x, \gamma_y, \lambda_x, \lambda_y\} \mid \{\alpha_w, \alpha_h, \beta_w, \beta_h\}\right] = \sum_{k=1}^K \eta_k \hat{\Sigma}_{\{\hat{\gamma}_x, \hat{\gamma}_y, \hat{\lambda}_x, \hat{\lambda}_y\}, k} \quad (3.20)$$

with η_k , the weight of the k -th Gaussian component through the mixture; $\{\hat{\gamma}_x, \hat{\gamma}_y, \hat{\lambda}_x, \hat{\lambda}_y\}$, the conditional expectation of $\{\gamma_x, \gamma_y, \lambda_x, \lambda_y\}$ given $\{\alpha_w, \alpha_h, \beta_w, \beta_h\}$; $\hat{\Sigma}_{\{\hat{\gamma}_x, \hat{\gamma}_y, \hat{\lambda}_x, \hat{\lambda}_y\}, k}$, the conditional covariance of $\{\gamma_x, \gamma_y, \lambda_x, \lambda_y\}$ given $\{\alpha_w, \alpha_h, \beta_w, \beta_h\}$. The generalized form of the motions required only weights, means, and covariances of the Gaussian components calculated through the EM algorithm.

3.4.2.3 Robot movement

Once we have obtained the entrance and exit coordinates to wind up the selected objects, we have the complete information needed in order to make the robot repeat the task using inverse kinematics. We use Trac-IK (Beeson and Ames, 2015) as the inverse kinematic motor. The planner is RTT connect (Kuffner and LaValle, 2000) from the OMPL library (Sucan et al., 2012). The planner includes an obstacle avoidance algorithm, in order to avoid obstacles already modeled in the system. We use MoveIt (Chitta et al., 2012) as the interface for planning and visualization in a virtual environment. With our solution, once the preprocessing phase is completed everything is handled autonomously from the robot inverse kinematics or kinesthetic teaching.

3.4.3 Results

Since the project is structured as a challenge, we needed to obtain the best results in the shortest time in order to achieve a good score.

3.4.3.1 Lab scenario

In the lab scenario, a person shows five arbitrary paths previously selected from an external subject by moving the end effector in a 25-peg grid for a maximum time of 1 minute. A set of metrics has been selected to compute the performance of the system. *Metric I* measures the mean time needed to compute the information provided by the camera network system after the demonstration stops. *Metric II* measures the mean time needed to update the model. Learning frameworks are usually based on probabilistic models built from a series of previous demonstrations called a training

set. An initial training set of 40 examples has been used as a basis to compute the robot trajectory. However, it could not cover all possible paths, in those cases the model needs to be updated. Moreover, the operator should be able to check the validity of a novel demonstration as soon as possible. *Metric III* measures the mean number of examples needed to learn a selected path in addition to the initial demonstration. The targets for each metric have been selected by looking at the expectation of the industrial partner and taking into account the state of the art in the field.

The time needed to compute the data recorded by the camera network was a mean of 56.24 s. We are able to provide an updated model starting only by the initial model and the data acquired during the last demonstration in 2.20 s. Nevertheless, the initial model has been always sufficient in order to compute the correct path for all five different paths, resulting in no additional demonstrations. The system guarantees a high success rate, high responsiveness, and low human effort. In fact, even in the worst cases, we overperformed the targets by obtaining 58.21, 2.21 s, and 0 additional demonstrations, respectively, for Metrics I, II, and III. The results are summarized in [Table 3.2](#).

3.4.3.2 Industrial scenario

The field test was meant to prove the robot capability to work with different sizes and characteristics of coils, and the correctness of both the pick and place tasks. Tests concentrated on the winding and pick and place of the coils ([Fig. 3.15](#)). A monitor shows wire tension during winding operations, in order to identify in real time picks that could break the wire. The performance was tested in terms of productivity, repeatability, reduced manufacturing costs, flexibility, and setup time. At the end of each winding process, the coil was compared with standards from actual industrial manufacturers by checking copper fill factor, inductances, resistances, and conductance at high voltage ([Table 3.3](#)). In particular, the copper fill factor is the ratio of the copper conductor area over the total slot area. For a section of coil, the copper fill factor is computed as $CFF = \frac{nS}{bh}$, where n is the number of copper turns (conductors); S is the part of cross-section composed by copper conductor; b is the base of the cross-section of a coil slot; h is the height of the cross-section of a coil slot. During the tests in Stuttgart, we were able to

Table 3.2 Final results for the lab scenario.

Metric	Description	Achievement	Worst case
Metric I	Time needed to extract the demonstrated trajectory	56.24 s	58.21 s
Metric II	Time needed to update the robot model	2.20 s	2.21 s
Metric III	Number of additional demonstrations	0	0

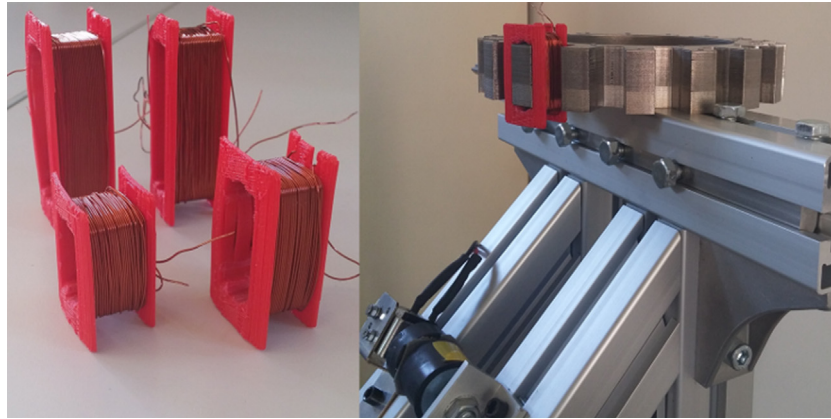


FIGURE 3.15 A set of wound coils ready for testing and a coil mounted on the stator.

Table 3.3 Results obtained during testing in the industrial scenario.

Metric	Manufacturer	Our system
Number of stators wound (8 h)	7	15
Correctly wound coils	90%	50%
Mean copper fill factor	0.2	0.5
High voltage	Pass	Pass
Resistance	Pass	Pass
Repeatability	20%	100%

reach a copper fill factor of 0.5. For electric motors used in standard applications, the copper fill factor is usually around 0.2. Moreover, we achieved a valuable advantage in terms of productivity and repeatability. At the current state, the production system in the manufacturer facility is able to wind seven stators in 8 hours. In our case, the robotic arm provides 15 completed stators every 8 hours. Finally, the repeatability was increased in a very significant manner due to the robotized approach. On the other hand, we faced a major problem with an increased number of faulty products. The results certainly could be improved with more accurate tuning of the overall system, but some parts of the framework should be revised in order to avoid failures. A simple example regards the material used for the coils. It was too fragile for the robotized procedure and sometimes it broke while winding the copper wire. The breaking problem could be avoided by 3D printing with a different material in order to find a solid structure. However, it is worth noting that the copper material (the most expensive one) used for the spare parts can be recycled in the very same process, and it was not wasted.

Another very important aspect of our system is the high flexibility provided with respect to industrial winding machines available in the market. The capability to switch between different types of motors with minimum cost for additional tooling is essential. Commercial winding machines usually provide very limited flexibility, with expensive additional tools required for winding different stator types. Moreover, the time needed for switching from one tool to another is quite long, taking from some hours to a day. With our system, a complete change of the entire production from a motor type to a different one required about 15 minutes, reducing drastically the minimum number of pieces for a sustainable production, and opening the market to SME with a low margin of investment.

3.5 Conclusions

In this chapter, we have presented a robot learning framework able to acquire information from the outer world and to generalize and understand it, obtaining in response a coherent robot motion. A robust preprocessing phase has been developed in order to clean and smooth the signals from variability due to noise or outliers. By removing artifacts, we have been able to highlight the particularly common characteristics of the specific motion along several different trials. The refined signals have been used to train offline a probabilistic model, namely a GMM, able to represent the signal as a weighted sum of Gaussian components. A regression technique, namely GMR, has been used to continuously estimate the joint bending angles to control a robotic device. We tested the proposed framework in two relevant industrial case studies: (1) the automatic assembly of a car door with its module, and (2) robotizing the manufacturing process of electric machines, in particular winding of coils on stator or rotor cores. In both cases, the proposed system can keep the costs low, while improving the production and flexibility as part of the Industry 4.0 paradigm.

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The tolerance scheduling problem for maximum lateness in Industry 4.0 systems

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4.1 Introduction

Industry 4.0 is a new production paradigm that promotes the digitalization of current industrial systems, in order to improve substantially their productivity and flexibility. This process has been pushed ahead by new technologies that are poised to change the very concept of production, like cyber-physical systems (CPS) and the Internet of Things (IoT). CPS link the physical aspects of production processes to digital platforms on which they run their virtual twins. Thus, CPS integrate in a single space the physical and digital ones (Lee et al., 2015;

Platzer, 2018). The IoT, in turn, facilitates the connection of different CPS, transmitting the real-time data collected by sensors in the physical space. The CPS will take care of most decision-making processes, particularly routine ones (Rossit and Tohmé, 2018). All this yields smart manufacturing systems, running autonomously. In this setting it becomes necessary to reconsider traditional planning methods, in particular those addressing scheduling problems. The scheduling problem is the last decision-making phase previous to the execution of production plans. It involves a very short time horizon, relating work orders (that agree with the requirements of customers) to physical resources of the organization (Pinedo, 2016). It is natural to conclude that these aspects make scheduling decisions susceptible to be impacted by Industry 4.0 developments (Liu et al., 2019).

Scheduling problems require finding solutions to the problem of allocating work orders on machines, intending to achieve assignation efficiency according to some performance metric. Once a solution has been found the schedule is executed. Then, unforeseen events and other real-world contingencies (machine breakdowns or delays, for instance) may affect the normal implementation of the plan. Then, rescheduling processes have to be run in order to reassign jobs to other machines (Vieira et al., 2003; Ouelhadj and Petrovic, 2009).

Traditional approaches do not contemplate systems in which there is a fluid interaction between the physical and virtual aspects, where the latter can be represented by spaces of decision. The information obtained in the physical space modifies, in real time, the parameters of the cyberspace, leading to new decisions that affect the execution in the physical space. This loop is a feature of Industry 4.0 technologies. But this real-time connection generates an excess of information that might trigger a reschedule. The *tolerance scheduling problem* (Rossit et al., 2019a) consists of taking up the information about unexpected events, evaluating their magnitude according to the schedule being executed at the moment in which they arise. Rossit et al. (2019a) formulate this problem in full detail, but in this chapter, we intend to generate mixed-integer models and run numerical experiments highlighting the virtues of this scheme of tolerances. As a base case we will consider the single machine scheduling problem in which maximum tardiness is the objective.

4.2 Industry 4.0 production environments

Industry 4.0 involves a paradigm change in production in which CPS become the main production assets. Networks of wireless sensors running on IoT systems convey the information about the physical production processes to the digital information systems of the companies (Wang et al., 2015). This means that the state and evolution of production processes can be assessed in real time.

The main difference of Industry 4.0 with its predecessors is its high degree of decentralization, which distinguishes it from the more traditional hierarchical

structures. Here the agents are connected among them as well as to decision centers, residing in the Cloud, which provides computational services over networks, in particular the Internet. This allows, in turn, to virtualize and dynamically scale up resources. Companies can, then, request resources on the fly, without incurring sunken costs and pay only for the resources actually used (Wang and Wang, 2018). The IoT provides the interconnection of the different technologies in use in production processes, ensuring the intelligent on-line integration of the corresponding devices and monitoring work orders in real time (Ivanov et al., 2018).

Big Data techniques are used to explore and detect patterns in large nonhomogeneous data bases collected on-line. These techniques detect patterns in cases in which traditional statistical methods cannot be of practical use, by using powerful and fast hardware. In the case of fabrication, Big Data methods are very useful to process the abundant data generated in production processes (Wang and Wang, 2018). One of the main sources of these data is the use of remote storage and recovery radio-frequency identification devices (RFID), namely RFID labels, cards, or transponders. The identity of an object (very much like its serial number) can be transmitted to others through radio transmissions, allowing the relevant exchange of information among moving objects at long ranges (Zhong et al., 2013).

4.2.1 Cyber-physical systems

Unlike the traditional integrated systems, in which the components tend to be independent, CPS are networks of interacting physical I/O elements. The adoption of “smart” CPS in different industries (airspace, automobile, chemical, energy, infrastructure, transportation, etc.) stimulates innovation and competence in them. Of particular interest for us is the design of smart production lines in which a single machine can perform several tasks, communicating with other units and coordinating activities (Wang and Wang, 2018; Rossit et al., 2019c).

A precise description of CPS can be given in terms of the five-level architecture of Lee et al. (2015). These levels, as illustrated in Fig. 4.1, are: (1) connection level; (2) conversion level, (3) cyber level, (4) cognition level, and (5) configuration level.

The connection level compiles information about the environment, drawing it from sensors, controllers, and the like. This level requires well-designed protocols to manage the different types of data and select the right sensors. The conversion level is where those data are transformed into useful information, yielding knowledge about the actual behavior of the machines. The cyber level plays a central role in the architecture, collecting information from all the components of the system. The fourth level generates the deep knowledge of the system, which can be used by expert users in support of decision-making processes. The final level is in charge of sending back information from the cyberspace to the physical space, acting as a *resilience control system* (Almada-Lobo, 2016).

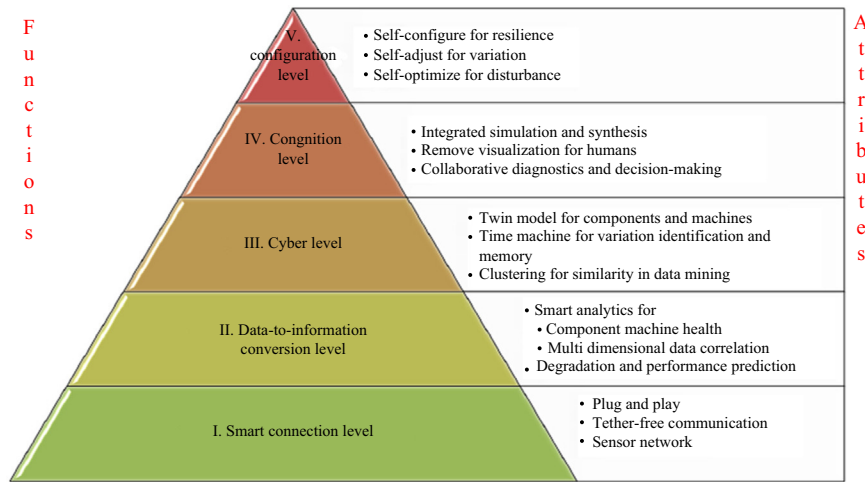


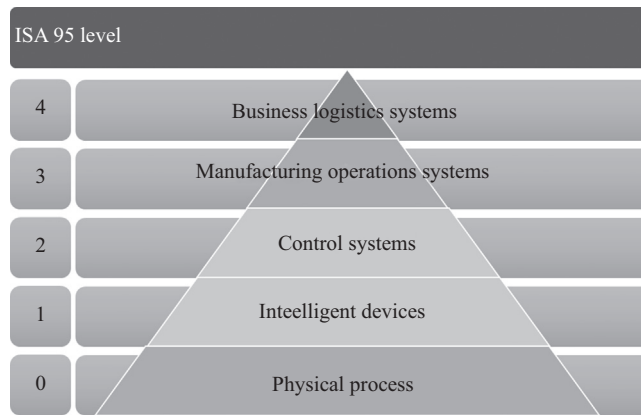
FIGURE 4.1

Architecture of cyber-physical systems (Lee et al., 2015).

4.2.2 Cyber-physical production systems

The possibility of unifying the behavior of industrial information systems with physical production assets in CPS led to the extension of the concept of cyber-physical production systems (CPPS) (Monostori, 2014; Monostori et al., 2016; Rossit and Tohmé, 2018). These incorporate different business functions into a single system built up from CPS (Monostori, 2014). Among those business functions we can find those described as manufacturing execution systems (MES), which are in charge of planning, executing, and scheduling production processes. To show how a CPPS can, in a quasiautonomous way, schedule production processes, we illustrate this by means of the control standard ANSI/ISA-95, a well-known architecture in production systems.

The ANSI/ISA-95 is a standard that can provide a framework for an automated interface between production facilities and control systems. It can yield common ground for the communication of all the participants in a production process and gives a representation of how information can be modeled and used. It organizes the different levels of decision-making hierarchically. It is based on the “Purdue Enterprise Reference Architecture” (PERA), which distinguishes five levels, as shown in Fig. 4.2. Level 0 is associated with the physical process of manufacturing. Level 1 involves the intelligent devices that measure and manipulate the physical processes that are located. Typical instruments at this level are sensors, analyzers, effectors, and related instruments. Level 2 represents the control and supervision of the underlying activities. Systems acting on ISA-95 Level 2 are supervisory control and data acquisition, programmable logic controllers, distributed control systems, and batch automation systems. Level 3 involves the

**FIGURE 4.2**

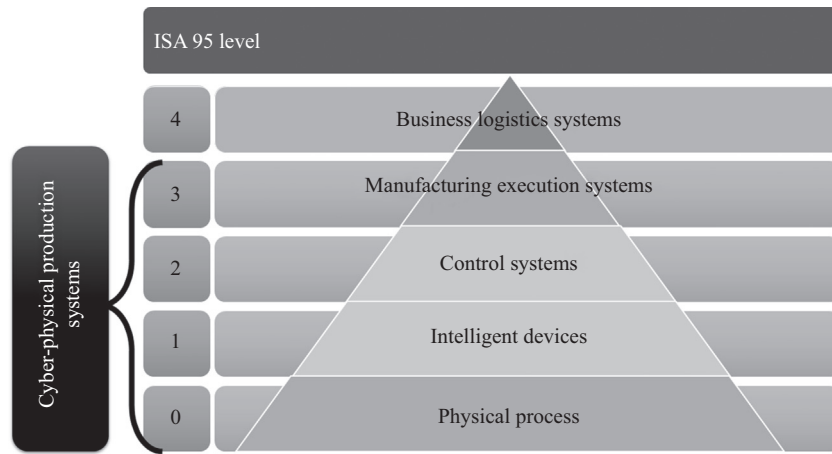
Control structure ANSI/ISA-95 (Rossit and Tohmé, 2018).

management of the operations and the production work flow in the production of the desired products. Some of the systems comprised at this level are batch management, manufacturing execution/operations management systems (MES/MOMS), the laboratory, maintenance and plant performance management systems, data historians, and related middleware. This level has special importance for our work, since it is here where the scheduling process takes place. Finally, level 4 is associated with the business activities of the entire firm. This architecture represents, in a synthetic way, the different activities and functions of a production system. In addition, it establishes the way in which the different levels communicate; in traditional production settings, in particular, each level interacts only with its adjacent levels (Rossit and Tohmé, 2018; Rossit et al. 2019d).

4.2.3 Decision-making in cyber-physical production systems

CPPS change the way in which decisions are made in the realm of industrial planning and control. To introduce our view on this topic, we show in Fig. 4.3 the levels of ISA-95 that should be incorporated into CPPS. This integration ensues from the capacities of CPPS, which can enact physical processes (level 0), measure and handle the instruments reading the physical processes (level 1), and implement control actions over its operations (level 2). Furthermore, given the computing power of CPPS, they will also be able to plan, evaluate, and manage the entire production process (level 3).

This integration of functionalities will yield direct benefits, as for instance increasing the flexibility of the production system in response to unexpected events; or the higher integration and transmission of information, given that a CPPS by itself can translate the data obtained at level 1 into the higher-level language used at level 3, bypassing the adjacency constraints inherent in PERA.

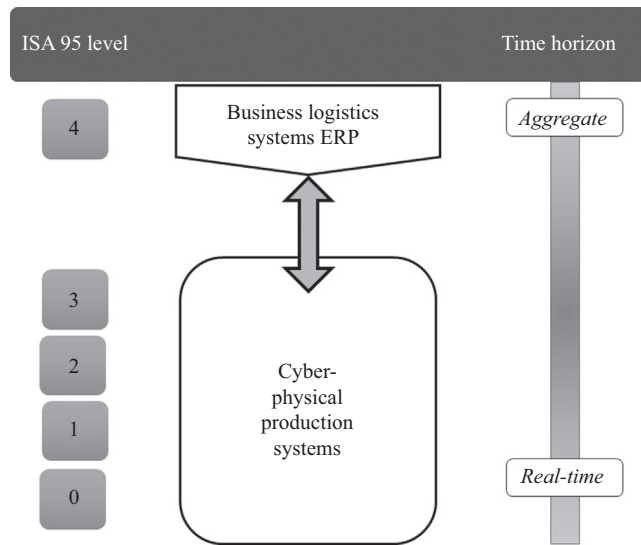
**FIGURE 4.3**

Control structure of a CPPS.

On the other hand, decision-making, focused on production planning, will be also impacted by the development of Industry 4.0. This will give rise to a new structure, which, while keeping PERA's levels, will be managed by two large systems: Enterprise Resource Planning (ERP) and the CPPS. Fig. 4.4 illustrates this.

Fig. 4.4 shows that the decisions about both the aggregate level and the goals to be pursued will be handled by the ERP systems (tuned to smart manufacturing environments). All other decisions will be automatically and systematically run by CPPS, including the execution of the production plan in real time. In this structure, the CPPS can be seen as a set of autonomous elements collaborating to reach the goals set by the ERP system. This means, in particular, that current MES, which take care of dispatching work orders and their scheduling in the shop floor, will be absorbed by CPPS. This will yield information of better quality, useful for both making the decisions at this level and minimizing response times, increasing the flexibility of the entire system.

A good deal of the decisions made by ERP systems (as inventory control, management of databases, handling information about suppliers, etc.) will be managed by CPPS. But we leave them separated as to indicate at what point the system becomes autonomous and up to which human interventions may be needed, particularly in the area of production planning. The linkage with human decision-makers will be at the aggregate or strategic level. They will define the goals and guidelines for the firm and the system. An ERP system will get them and will translate these guidelines for the rest of the system, in particular to the CPPS that handle the production system. The latter are thus not completely autonomous since they keep an open loop with the ERP system, at least on production planning (see section 2.4.1.1 in Framinan et al., 2014). Basically, this procedure

**FIGURE 4.4**

Distribution of ISA-95 levels between ERP and CPPS. The representation of time is drawn from the model of the Manufacturing Enterprise Solutions Association (MESA) International.

plans and controls the fabrication tasks in a given manufacturing infrastructure, but not planning the infrastructure itself. In this line, [Almada-Lobo \(2016\)](#) postulates the absorption of MES in Industry 4.0 systems. On the contrary, higher levels of management, defining more general aspects of the fabrication, should not be included.

Despite this, since CPPS integrate horizontally the three levels of ISA-95, they will gain access to quality control systems, inventory management, maintenance planning, and the historical records of these systems. This endows CPPS with the ability to handle data that can influence both the schedule as the inventory issues that may generate delays or scarcity of resources, affecting its performance ([Kuo and Kusiak, 2019](#)). The same is true for real-time monitoring systems linked to maintenance, in which the stress on machines may force an earlier maintenance stop, affecting their availability ([Lee et al., 2017](#)). Even if the impact of these aspects on the schedule may be indirect, it is clear that having access to data on them helps to find better schedules. Our design is based on the incorporation of these new functionalities into CPPS and on their redirection toward obtaining improved scheduling processes.

Besides these new capabilities, CPPS handle the classical data required to solve the scheduling problems defined in [Fig. 4.3](#), but with serious advantages over traditional approaches. Since CPPS control physical processes and collect data on them, their computing power allows also to process this information. This

yields an integrated view in which data are collected by the same entity that will execute the actions that ensue from processing them. Furthermore, the decision-making process can be also carried out by CPPS. Thus, these systems will at the same time collect the data, process them, make decisions, and execute them. This vertical integration improves the quality of the results and the entire performance of the production system. Our DSS based on these potentialities of CPPS is intended as a step toward implementing the aforementioned vertical integration in smart manufacturing environments.

4.3 Scheduling

In this section we present a brief review of some contributions to the literature on scheduling in order to frame our proposal. Deeper analyses of scheduling in Industry 4.0 environments can be found in [Dolgui et al. \(2018\)](#), [Ivanov et al. \(2018\)](#), [Liu et al. \(2019\)](#), [Rossit et al. \(2019b\)](#), [Uhlmann and Frazzon \(2018\)](#), [Waschneck et al. \(2017\)](#), and [Zhang et al. \(2017\)](#).

In the context of flow shop production systems, [Luo et al. \(2015\)](#) analyzed a hybrid job shop scheduling problem in which jobs arrive dynamically and the operations on machines are not continuous. Information is obtained in real time through RFID technologies. To solve the problem, these authors introduce a multiperiod hierarchical programming mechanism that divides the planning horizon in shorter periods. The shorter period decisions are left to the shop, while managers take care of the longer horizon. In both cases the decision-makers optimize the timing of activities.

[Wang et al. \(2016\)](#) introduce a Petri nets-based programming framework to solve IoT-enhanced hybrid flow job shop problems. This allows them to run in real time an Ant Colony algorithm, in which pheromones are restricted to avoid an inferior result in the search for solutions.

[Framinan et al. \(2017\)](#) study the impact of real-time information in the generation of reschedules in problems in which the goal is to minimize the makespan. Their main contribution is the quantification of the advantages of collecting data in real time to reschedule some jobs. Their results show that rescheduling dominates running the same schedule, conditional on the variability of processing times. A larger variability reduces the benefits of rescheduling. [Framinan et al. \(2019\)](#) present rescheduling strategies that maximize the benefits of collecting data in real time. One of them uses the critical path as a tool. Reschedules are triggered only if the difference between real and expected processing time affects the critical path.

[Fu et al. \(2018\)](#) study a two-objective flow shop problem in which processing times depend on Industry 4.0 time and uncertainty. They find solutions using their Fireworks algorithm.

Other contributions focus on job shop environments. [Cuihua et al. \(2016\)](#) studied scheduling problems in which the pieces to be processed are identified using RFID, with each piece requesting the next operation. These authors present a double genetic algorithm improving the results with a single algorithm.

[Ivanov et al. \(2017\)](#) study a job shop problem in Industry 4.0 environments using control theory, allowing them to find efficiently solutions for the production of highly personalized goods. [Leusin et al. \(2018\)](#) consider a multiagent system incorporated in a CPS to solve dynamic problems in the shop. To do that they use a data exchange framework guaranteeing the efficient integration of the system. This allows them to exchange real-time information about IoT mechanisms, self-configuring the system and managing disruptions along the production line. This produces flexibility, scalability, and efficiency gains over more traditional procedures.

While only a few, these contributions show the interest in adapting the techniques of scheduling to the challenges posed by Industry 4.0 environments. Our own contribution goes in the same direction, since it seeks to generate support tools for decision-making in scheduling, profiting from real-time information gathered from the shop floor.

4.4 The tolerance scheduling problem

Industry 4.0 allows reacting in a fast way to disruptive events that may happen during the execution of production plans. The literature on dynamic scheduling provides the framework for our own proposal, which is to develop tools to solve what we call the tolerance scheduling problem.

4.4.1 Dynamic scheduling

While the problem of dynamic scheduling has been studied in the past ([Vieira et al., 2003](#); [Ouelhadj and Petrovic, 2009](#)), the possibility to obtain real-time information has renewed interest on the problem. A classic example in the literature on dynamic scheduling arises when a machine gets offline, for example, because of a failure. Then the operations assigned to that machine have to be redirected to others, forcing a reschedule of the production process. This problem is far from trivial and if incorrectly solved can cause large losses ([Vieira et al., 2003](#)).

Disruptive events can have two main causes: problems with resources in the shop or problems with the jobs to be carried out. Among the former we have machine failures, employee sickness, unavailability or lack of tools, load limits, delays in arrivals, scarcity of materials or defective materials, among others. Problems with the jobs include cancellations, urgent requests, due date changes,

tardiness or earliness of jobs, changes in priorities, changes in processing times, etc.

There exist different strategies addressing the issue of rescheduling tasks in the face of disruptions in the production line. Some are purely reactive, just focused in sending out new tasks, without starting with an initial schedule.

In fabrication systems, instead, predictive-reactive strategies are more common. They proceed in several stages, at which previous schedules are revised in response to real-time events. In the first (predictive) stage a schedule is determined without assuming possible disruptions. In the next reactive stages the original schedule is modified assuming no further disruptions will appear. This is repeated every time a reschedule is needed (Li et al., 2015).

4.4.2 Inverse scheduling

The tools of inverse optimization are adapted to handle the problem of inverse scheduling (Ahuja and Orlin, 2001). The general problem of inverse optimization consists in inferring the values of the parameters of a model (e.g., cost coefficients, values of constraints, etc.) up from observable optimal values of the decision variables. That is, given a solution, determine the parameters under which the model yields that solution as an optimal outcome.

As already said, the values that are to be determined correspond either to coefficients of objective functions or of the constraints. In scheduling the latter is usually the case, with the adjustable parameters being processing times (Koulamas, 2005) or due dates (Brucker and Shakhlevich, 2011)

A usual requirement is that the sought parameters should be restricted to belong to given intervals, Brucker and Shakhlevich (2009), for instance, analyze the time assignments on a single machine so as to minimize the total tardiness of the sequence of operations. For a given job j , its tardiness is the additional time required to finish it, in excess of the due date. Formally, given a due date d_j and a schedule π , the tardiness of j is:

$$L_j(\pi, d) = C_j(\pi) - d_j \quad (4.1)$$

where C_j is the time required to finish j in schedule π , while d is the vector of due date of all jobs. Then, the maximal tardiness is given by:

$$L_{\max}(\pi, d) = \max_{j \in N} \{L_j(\pi, d)\} \quad (4.2)$$

A classical scheduling problem amounts to finding π^* , such that $L_{\max}(\pi, d)$ is minimal, that is:

$$L_{\max}(\pi^*, d) \leq L_{\max}(\pi, d), \quad (4.3)$$

for every other schedule π .

In the solution of the inverse scheduling problem the processing time p_j and the due date d_j are obtained from the given schedule π . To see this, assume that

in the single machine case only due dates can be adjusted and that for each job j , $d_j \in [d_j; \bar{d}_j]$. Therefore, the adjusted due date has to satisfy $\hat{d}_j \in [d_j; \bar{d}_j]$ for each j , yielding $\hat{d} = (\hat{d}_1, \hat{d}_2, \dots, \hat{d}_n)$. The Euclidean distance to the original d , denoted $\|\hat{d} - d\|$ must be minimized. Then, the inverse scheduling problem is:

$$\min \|\hat{d} - d\| \quad (4.4)$$

$$s.t. L_{\max}(\pi, \hat{d}) \leq L_{\max}(\sigma, \hat{d}), \quad (4.5)$$

for any schedule σ , $d_j \leq \hat{d}_j \leq \bar{d}_j$, $j \in N$.

Other metrics, instead of the Euclidean one, could be applied to measure the deviation to be minimized. This might change the results (Ahuja and Orlin, 2001).

Another kind of inverse scheduling problem arises when the goal is to achieve a given level of the objective function. Up from an initial solution, the parameters are adjusted so as to reach the desired level. In the case in which the objective is to minimize tardiness on a single machine the problem amounts to finding $\hat{d}_j \in [d_j; \bar{d}_j]$, such that the value of the objective function $L_{\max}$ is better or equal than L^* . That is:

$$\min \|\hat{d} - d\| \quad (4.6)$$

$$s.t. L_{\max}(\sigma, \hat{d}) \leq L^*, \quad (4.7)$$

for any schedule σ , $d_j \leq \hat{d}_j \leq \bar{d}_j$, $j \in N$.

Similar problems have been stated and solved for other parameters. For a sample of inverse scheduling problems, see Heuberger (2004).

4.4.3 Tolerance scheduling

The direct connection between the decision-making processes with the shop floor makes rescheduling processes event-driven. This means that rescheduling is triggered by events modifying the setting of the initial schedule. To automatize this process, we need criteria for the identification of the events that lead to reschedules, which have to be defined beforehand and must thus be related to the essential features of the event, whether it originated in the production resources or in the jobs to be carried out. Once identified, an event may belong to the class that triggers reschedules, but even so, its magnitude may not merit starting the rescheduling process. This becomes an additional source of instability, exposing the production process to many uncertainties affecting the plan (Pinedo, 2016; Framinan et al., 2014). To react at each an event disturbs the shop floor and affects the efficiency of the system (Rossit et al., 2019e). Our take is to address a new scheduling problem in which the solution is tolerant of a range of events that by themselves are deemed as triggers of rescheduling.

This *tolerance scheduling* problem starts with an initial solution (optimal or near-optimal). The goal is to generate a range of tolerances, mainly for the parameters of the model. As with the specification of tolerances for manufactured goods that allow for a range within which the good is still considered appropriate, here we allow for a certain degree of imperfection in the plan actually carried out. Consider, for instance, situations in which the actual processing times differ from the specifications used to solve the original scheduling problem. This event has an impact on the performance of the production process (e.g., worsening the makespan), which would call for rescheduling the plan. But it is worth pondering whether the gains of doing this outweigh the costs of rescheduling.

Consider again the single-machine scheduling problem of Brucker and Shakhlevich (2009). In the inverse scheduling problem, we seek to find the adjusted delivery dates of each job, d_j , in order that a given schedule π becomes optimal. In the reverse scheduling, instead, we seek to make minimal adjustments to the delivery dates and the schedule to ensure a certain range of values for the objective function. In our case we seek tolerances for the parameters ensuring that the original schedule remains acceptable and thus no rescheduling is necessary.

Formally, given an optimal or near-optimal schedule π , $F(\pi) \approx L^*$, and the families of parameters d_j and p_{ij} , we seek a maximal interval of variations for them, we also incorporate an *inertia factor*, δ , expressing the weight given to the stability of the system (Rossit et al., 2020). A high δ indicates that the design favors a high stability (high inertia), meaning that few events can trigger reschedules. Then:

$$\max \|\hat{d} - d\| \quad (4.8)$$

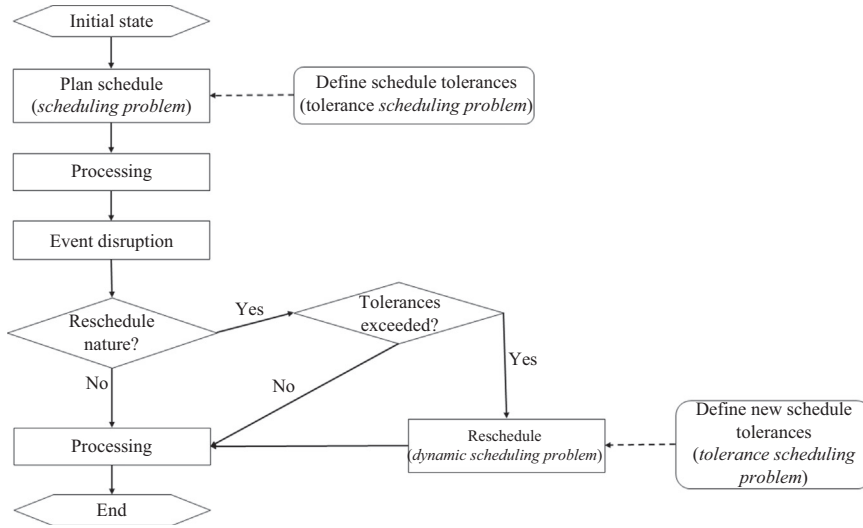
$$s.t. L_{\max}(\pi, \hat{d}) \leq L_{\max}(\sigma, \hat{d}) \cdot (1 + \delta), \quad (4.9)$$

$$L_{\max}(\pi, \hat{d}) \leq L^* \cdot (1 + \delta), \quad (4.10)$$

for any schedule σ , $d_j \leq \hat{d}_j \leq \bar{d}_j$, $\delta \geq 0$, $j \in N$.

That is, the goal is to maximize the distance between the d parameters, while ensuring that schedule π improves the original objective function up to an inertia factor $\delta \geq 0$. This provides a tool that not only detects possible rescheduling events but also determines whether or not to proceed with the rescheduling process. The choice of δ is not arbitrary: it must be proportional to the weight given to the *inertia* of the production process. That is, if the idea is to reschedule only at high levels of disruption (high inertia), δ must be large. On the contrary, a low inertia system should be more ready to react, which requires a lower δ .

This procedure is rather easy to automate, providing another tool to be added to the DSS embedded in the CPPS, making the latter more prone to autonomous behavior. The value of δ should, in that case, be set at the design stage (Fig. 4.5).

**FIGURE 4.5**

Tolerance scheduling problem embedded into a dynamic scheduling system.

4.5 Application case: single machine scheduling minimizing $L_{\max}$

Consider n jobs on a single machine, with the objective of minimizing maximal lateness ($L_{\max}$). We look for optimal schedules assuming that the shop floor is not free of potential disruptions. We consider here the possibility of failure of the machine, a case commonly analyzed in the literature (Zandieh and Gholami, 2009; Ahmadi et al., 2016; Liu et al., 2017). This condition is unforeseeable and independent of the schedule of production.

The mix-integer formulation of this problem is as follows:

Set

J set of Jobs indexed by $\{j\}$

Parameters

p_j processing time of job j

d_j due date of job j

Ω large positive number

Variables

C_j Completion time of job j

$x_{j,j'}$ Binary variable, 1 if job j is processed after job j' , 0 otherwise

$$\min L_{\max} \quad (4.11)$$

s.t.

$$C_j \geq C_{j'} + p_j - \Omega \cdot (1 - x_{j,j'}) \quad (4.12)$$

$$C_1 \geq p_1 \quad (4.13)$$

$$x_{j,j'} + x_{j',j} = 1 \quad (4.14)$$

$$L_{\max} \geq \max(0; C_j - d_j) \quad (4.15)$$

Condition (4.11) defines the minimization of $L_{\max}$ as the objective function. Inequality (4.12) states the precedence constraint, which applies only if job j is processed after job j' (being thus $x_{j,j'} = 1$), while if that is not the case it becomes a dummy constraint. Constraint (4.13) ensures the completion of the first job. Eq. (4.14) establishes that j is processed either after or before j' , with the two possibilities being exclusive. Finally, (4.15) defines $L_{\max}$ for every job j .

The model given by (4.11)–(4.15) represents the classical scheduling problem, without assuming rescheduling or tolerances. Failures of the machine do not affect this setting but will be reflected in the actual finishing time C'_j , of the job j that was being processed during the failure. The completion times of the jobs after j will also be affected and will differ from the solutions to (4.11)–(4.15). The actual maximal lateness, $L'_{\max}$ will now be given, for every job j , by:

$$L'_{\max} \geq \max(0; C'_j - d_j) \quad (4.16)$$

A human scheduler would, in this case, evaluate whether to trigger a reschedule according to the needs and requirements of the firm. In the case of Industry 4.0 this decision will be made automatically by the system. For that, the tolerances have to be computed, considering the upper bound of the actual lateness $L'_{\max}$. The tolerances corresponding to schedule π [satisfying (4.11)–(4.15)], tol_{π} are given by:

$$tol_{\pi} = L_{\max} \cdot (\delta), \quad (4.17)$$

$$L'_{\max} \leq L_{\max} + tol_{\pi}, \quad (4.18)$$

where (4.17) expresses that the tolerance that allows to keep considering π as the valid solution (tol_{π}) must be the value of the objective function times an inertia factor δ . In consequence, the value of $L'_{\max}$ is bounded above as described by (4.18). If that bound is surpassed, a rescheduling alarm is triggered.

To illustrate this consider the following numerical example, in which 10 jobs have to be scheduled on a single machine. The processing and due times for these jobs are given in Table 4.1.

The values of the processing times have been generated, taking as a source Taillard (1993), who obtains p_j as draws from an uniform distribution over [1:99]. In turn, the due dates, d_j , obtain using the formula in Ruiz and Stützle (2008), according to which $d_j = \sum_m p_{j,m} \cdot (1 + random \cdot 3)$. In our single machine case we have $d_j = p_j \cdot (1 + random \cdot 3)$, where *random* is a random extraction from (0; 1).

To find the optimal solution we formulated the model in Pyomo (Hart et al., 2012) and implemented it in SolverStudio (Mason, 2013). As an optimization tool we ran GUROBI 8.1 on an i5 processor with 8 GB of RAM memory.

Table 4.1 Processing times and due dates

Job $\{j\}$	1	2	3	4	5	6	7	8	9	10
p_j	17	52	96	61	88	55	91	49	26	68
d_j	4	7	10	13	16	19	22	25	28	31

The optimal solution without disruptions yields $L_{\max} = 504$, with a schedule π : J8-J9-J2-J6-J1-J10-J7-J5-J4-J3. We considered an inertia factor $\delta = 0.15$. Then, $tol_{\pi} = 75.6$, and the upper bound on the objective function is $L'_{\max} = 579.6$.

Failures of the machine have been modeled with a Poisson distribution assuming three failures each 1000 time units, and times between failures have been modeled with an exponential distribution with mean $\lambda = 1/333$, that is, 333 time units between failures. This formulation is standard in the literature (Zandieh and Gholami, 2009; Ahmadi et al., 2016; Liu et al., 2017). We also modeled the reparation times, rep_i , for each failure i assuming a uniform distribution over $[30;70]$ in such a way that the expected value of reparations coincides with p_j , generating significant failure events. Following the usual procedures in discrete event modeling, we generated by simulation a future event list (FEL) (Zandieh and Gholami, 2009). We created a scenario with two failures in its FEL 2 with 170 time units between them.

First event. The simulation proceeds processing π , up to $t = 170$, at which the first failure happens, with a reparation time $rep_1 = 38$. This happens during the processing of the fourth job of π , J6. $C_{j=6}$ is initially 182, while after the repair it becomes $C'_{j=6} = 220$. To run a comparison, we implement first (instead of smart scheduling) a purely reactive strategy, which reschedules the production of the remaining jobs. This requires a slight modification of (4.13) applied to the first job *after* the repair:

$$C'_1 \geq p_1 + C'_{j=6} \quad (4.19)$$

In this case the first rescheduled job has to take into account the actual $C'_{j=6}$ since the machine will not be available before. The reactive-scheduler has to reschedule the remaining jobs, J1, J10, J7, J5, J4, and J3. The new schedule yields $L'_{\max} = 542$, and now the sequence becomes $\theta = J7-J5-J4-J4-J10-J1-J3$. Other than J3, all the jobs become reordered. This generates “noise” in the floor shop, forcing changes in the allocation of workers, in the request of materials, in the estimation of delivery dates, etc.

Our smart scheduling procedure starts by evaluating the magnitude of the disruption caused by the broken machine. Since $tol_{\pi} > rep_1$, there is no need to change the original schedule π . This implies that, upon the new values C'_j , $L'_{\max}$ is determined according with the original π . We obtain $L'_{\max} = 542.2$, which is practically the same value as that obtained by the reactive-scheduler, but without requiring major modifications in the routine of the shop floor. This shows that

this procedure captures the behavior of human schedulers, which after computing θ and getting a value of the objective function of 542, would not really choose to reschedule just for a gain of 0.2 time units, causing major changes in the shop.

Second event. The simulation proceeds processing π , up to $t = 378$, at which the second failure happens, with a reparation time $rep_2 = 66$. This happens during the processing of the seventh job of π , J7. $C'_{j=7}$ was 396 (including the first event), and now after the impact of the second event (second repair), $C'_{j=7} = 462$. The reactive-scheduler triggers a new reschedule for the still unprocessed jobs, J5, J4, and J3. Expression 4.19 becomes now $C'_1 \geq p_1 + C'_{j=7}$. The solution is a new schedule $\alpha = J4-J5-J3$ with $L''_{\max} = 608$.

In our smart scheduling approach we get $75.6 < 38 + 66$, surpassing the tolerance of the system, also triggering a reschedule. The solution will thus coincide with that of the reactive-scheduler. Again, our approach provides a good representation of what human schedulers would decide, with the obvious bonus that, unlike reactive-scheduling, it takes into consideration the impact of disruptions over the entire sequence of jobs.

4.6 Conclusions

In this chapter we analyzed the problem of rescheduling in the context of Industry 4.0 production systems. We presented a formulation of what we call tolerance scheduling, which allows the system to make autonomously decisions on when and if to change schedules of production in the face of disruptions.

We presented this alternative formulation in the context of the potentialities of Industry 4.0 and in particular CPPS, able to embody in their virtual components many functions proper of floor foremen and managers.

We illustrated the advantages of our formulation in an example of a single-machine scheduling problem with 10 jobs when the goal is to minimize maximal lateness. We compared our approach to the use of simple reactive reschedules, showing that implementing tolerance scheduling in CPPS can be beneficial for production processes endowed with the possibility of using Industry 4.0 tools.

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Digitalization and security: a new challenge for Mathematics 4.0

5

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5.1 Introduction

Industry 4.0 opens up new challenges for industrial as well as to applied mathematics applications.

The challenging questions addressed in this chapter include:

- How to analyze a huge amount of data?
- How to integrate data awareness, especially in mathematical models that push the optimization of processes?
- How to optimize the supply chain management and logistics?

Industry 4.0. provides the technical requirements, but mathematics increases the potential. This chapter will show that mathematics can be seen as a core element of Industry 4.0.

5.2 The role of mathematics in Industry 4.0—a special kind of decision-making

Based on cyber-physical components, automated production and the huge amount of data available (e.g., historical data), Industry 4.0 requires some form of technical approach for its interaction with the components. A technical framework which runs permanently in the background is therefore necessary, and mathematical tools make this possible. An even greater gain may be using these data to define, for example, what and how many products to produce, which to produce first, how to deliver the products, how much of each component should be in stock, etc.

These kinds of decision-making are part of the daily routine of most companies. Using incisive mathematical analytical analysis for the decision-making process would be a great help for a number of industries. This analytical analysis is done by mathematical Industry 4.0, which can be seen as a tool that transforms data into decision-making.

The decisions made are always rational, implying that they return the greatest profit in the most efficient way, and all decisions are in pursuit of the optimum results. The tool that transforms data into decision-making is the study of data—data

science. Within data science, methods of recording, storing, and analyzing data are researched.

This contribution shows that data science consists of more components than just mathematics.

Mathematics, statistics, computer science and engineering are all part of data science.

5.3 The mathematics of data science—challenges to Industry 4.0

Regarding the usage of different data sources concerning the production process of a single product, the following key questions regarding the variety of data come up:

- How to extract only the useful information?
- How to integrate the knowledge which is already available because of data?
- How to secure data errors and uncertainty? (How to make data safe?)
- How to generate additional knowledge from new data?

5.3.1 Making decisions—preparation of data

The importance of mathematics in the industrial field steadily grows. Currently, most companies utilize the innovative potential of mathematical tools, including statistics, modeling, simulation, optimization, and statistics. Before a decision could be taken, data needs to be prepared. There are different options when it comes to the preparation of data: data mining, data analysis, programming, use of AI, machine learning, and data research are just a few of various possibilities to set up structures.

Mathematical tools are a key source for creating such fundamental structures: from optimizing a device and shortening developing times to reducing costs, mathematics plays an important role in creating patterns (Figs. 5.1 and 5.2).

Figure 5.2 shows some of mathematics which influence data science:

Within Industry 4.0, mathematics is seen as a basis for the used technologies. Emerging technologies like 3D printing, IoT, Big Data, virtual and augmented reality, digital twins, AI, machine learning, blockchain, automation, and robotics, are other technological developments that are often applied by companies and also have their foundations in mathematics.

Siemens is a good example of how international market participants use mathematics within their companies. This technology group has carried out research on the applications of digital twins. They use mathematical-computational models of technical mechanisms and devices. These mathematical models are simulated using computations for studying complex systems. The models are able to support milling robots in fine-tuning their tasks, for instance.

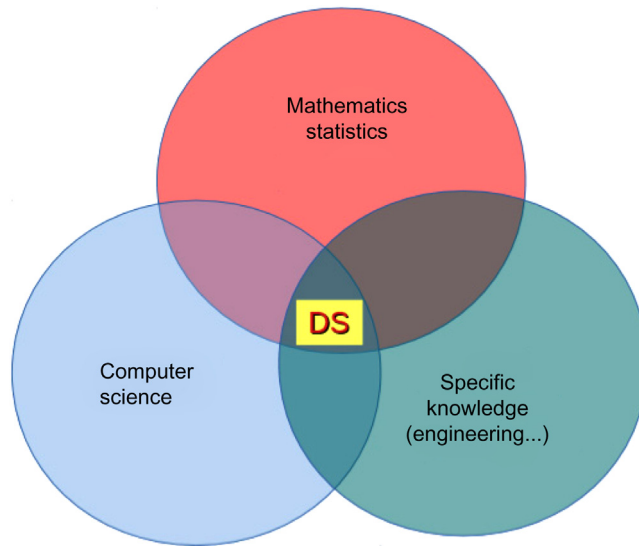


FIGURE 5.1

The components of data science.

Formaggia (2017) The mathematics of data science.

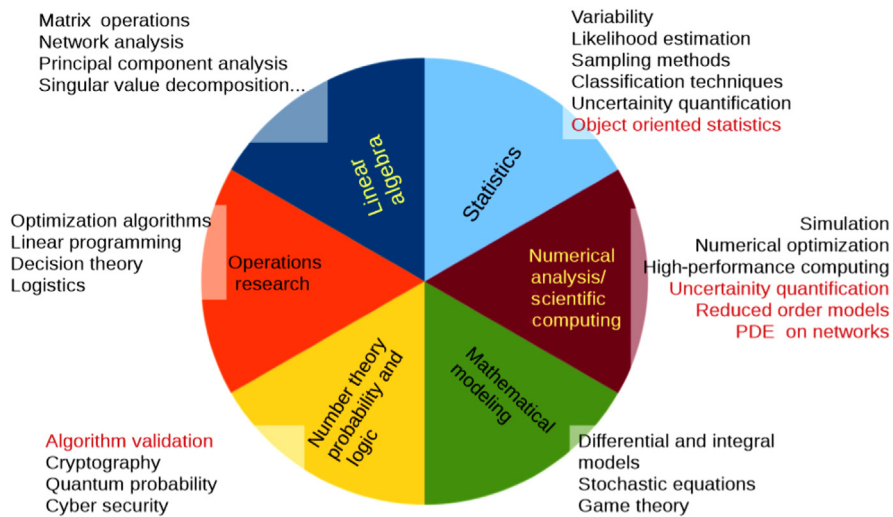


FIGURE 5.2

The mathematics of data science.

Formaggia (2017).

The generation of a digital network that will be constantly fed with data until the final step, firstly requires technical surroundings. However, the availability of a network and digitalization alone are not enough, due to the fact that these two components together will not be able to create intelligence. Additionally, the exclusive combination of these two inputs generates no added value. This is the point where mathematics is highly required, because in the final production step the machine should be able to make intelligent decisions autonomously. The extent of data available is constantly growing. As a result, the number of decisions that could be made increases as well. Creating a connection between current research and practice is essential for Industry 4.0. In particular, mathematical models and algorithms and their efficient hardware and software implementation play a fundamental role. With the help of statistics and machine learning, structural patterns in data can be recognized and thus made usable. This is a basic foundation stone of self-learning systems. Progress in mathematical optimization also offers decision-making aids today, even for the most complex problems:

What is produced and moved when, how, where, for which upcoming machine provided, in which order, at what price?

With the increasing networking of decentralized controlled systems, game theory is becoming increasingly important.

The prerequisites for Industry 4.0 must firstly be implemented in the form of a digitalization strategy. This strategy should specifically show which data is recorded, networked, archived, and visualized. In order to make optimal decisions from production and logistics to strategic levels, the importance of mathematics will inevitably increase. Only the combination of classic factory planning with methods of higher mathematics will enable the prerequisites for Industry 4.0 to be guaranteed.

5.4 Digitalization and security

5.4.1 Challenges and opportunities in the course of intelligent process optimization

Digitalization and small and medium-sized enterprises (SMEs)—what is a scientific approach to this topic (and an interesting area of tension, respectively)? The following fictional story is a good example during the holidays, having a core of truth in it. This example might seem somewhat amusing and far-fetched, however, it will lead to the core thesis of the contribution to follow.

5.4.2 A duck tale and Industry 4.0

Huey, Dewey, and Louie go on a long journey with their uncle Donald. They want to travel to a country of “unlimited possibilities,” for which they need to

request access authorization, making a stopover on their way. Usually this authorization is valid for two years. The request can be done online and is already optimized for various processes. Donald requested it for his three nephews, in order to have the permit before their departure. This permit remained valid for another year.

However, when the four of them arrived at the departure airport together, Donald was denied permission to depart, because his new passport (that he had applied for two months before), was no longer valid. . .

To what extent is this introductory story (which happened to the author in this or another form) connected to digitalization? Because it is based on a true story that could not be solved mathematically in an optimal way, it should be seen as a motivation to preliminarily follow up with this important topic area.

Critics might say that there is the possibility of requesting such a certificate at the airport, and also online. This would be a process that normally takes 2–3 days being accomplished in 2 hours. In our story, the time, even less than 2 hours, was not sufficient unfortunately, the time required was 15 minutes out. Though it would have been possible to receive the certificate successfully at the intermediate airport, this would have meant that, within this “online” process, an interacting component should have been integrated, that was not initially intended. This aspect should now be seen as leading to the integration of digitalization in SME.

This simple and fictional example shows how far digitalization has found its way into our lives, how we deal with it, and also which problems may be met. Several investigations and events have been documented showing that especially small and medium-sized companies in Germany have acknowledged the central strategic importance of digitalization ([Deloitte, 2016](#)).

5.5 What do we mean by “digitalization”?

First of all, digitalization means that processes and productions are “virtualized.” Here, especially the integration of data, data models, and IT-based decision-making supported by algorithms are of importance. In contrast to “digitalization,” the term “computerization” is used often, in which ICT and also Internet technologies are used purely for “support” of business processes.

It has become apparent that the initial example did not lead to an optimal solution because, for the most part, this process was exemplarily “computerized,” but has not appeared as a fully “digitalized” service yet. It is not possible to get an overall view of this process or to take any corrective action that may be necessary. This special digitalization level, according to ([BMW, 2017](#)), grows with the increasing size of the enterprise. Therefore, larger companies tend to digitize their enterprises more compared to SMEs exists only in one out of five SMEs, and in larger enterprises it reaches about 30%.

5.6 Efficiency enhancement and added value through digitalization

Digitalization should not only accelerate administration processes or implement them more effectively, it should also have economic advantages. In [BMW \(2017\)](#), the digital dividend for 20% of SMEs was explicitly considered, showing the fact that, thanks to digitalization projects alone, 160,000 new jobs, EUR 50 billion of additional turnover, and EUR 20 million worth of added value have been created.

Whether these figures correspond exactly to the reality cannot be precisely predicted from this interesting and very readable study, however the orders of magnitude alone point to the special potential associated with digitalization. As the initial example clearly shows, by taking digitalization not seriously enough or by reducing it to simple computerization, a huge amount of the possible connections might be lost.

5.7 Digital distribution channels

Probably the richest man in the world invested in a company more than 20 years ago, a company characterized by exactly two changes to the classic order process: an ordered book, for example, is not sent to the bookshop anymore, but instead is sent directly to the customer. Simultaneously, the distribution channel was increasingly digitalized. A “classic” product innovation did not initiate or accompany this process. However, this example shows impressively how also areas of online marketing, social media activities, and particularly the adaptive optimization of customer relations have gained in importance by the establishment of digital distribution channels. Based on the overall integration in various areas, a significant advantage for the future has been created, which is furthermore seen as a high potential for innovation. This week, the author had a digital menu in his hands for the first time, which has been in form of a tablet computer. One could turn the pages digitally, however the orders still had to be placed analogously. This example shows an already existing future potential, where one leads to a digital economy within the scope of data integration.

5.8 Digital economy and Industry 4.0

This digital economy is characterized by the following aspects according to [\(BMW, 2017\)](#)

- Virtualization of processes and products;
- Networking of people and things;
- Sharing of data.

What is important here is that these central areas should not be considered independently. The basis for this holistic approach is first of all the integration of data, underlying data models and algorithms for IT-based decision support. These structures are used to connect people with processes. The aim is to create an integration of the overall system on the basis of a holistic approach.

5.8.1 Strategic digitalization—intelligent tracking and complex security

Huey, Dewey, and Louie had to fly alone, although it may have been possible to solve the problem with human interaction in two parts of the process. For one thing, they had almost 90 minutes to get an overall insight. A holistic virtualization should therefore be combined with a continuous visualization. If “intelligent tracking” is implemented in such structures of a process—as is already the case in many leading logistics companies—one would have the possibility to integrate strategic action. For instance, with leading international logistics services, it is not only possible to “follow” the process but also to change methods of delivery, even shortly before the product is delivered. Such aspects may not be applicable for SMEs, but could generate a major competitive advantage.

5.8.2 Interaction and intelligent overall system

The overall system has to provide an opportunity for the interaction. Hence, the so-called interaction is of central importance within digitalization. In our example this aspect would be the fact that Donald could travel to the stopover, receive the relevant information there, and continue on his journey. Summarizing, one can therefore say that:

1. Digitalization is closely connected to the visualization of business processes.
2. The development of complex overall systems can be a trend-setting orientation for interactive overall systems.

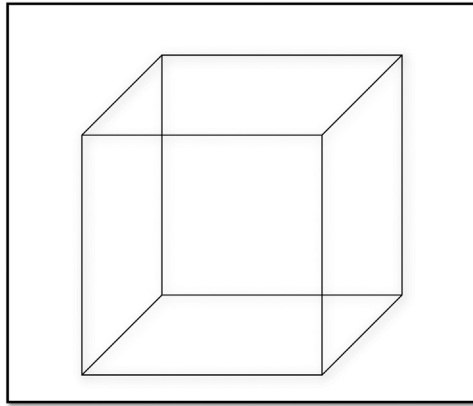
According to [IW Consult, 2018](#) these two areas can be seen in the context of the following chart:

Digital	Digital
Business models	Processes
Digital	Digital
Virtualization	Products

5.9 Digital processes as a supreme discipline— computerization versus digitalization

Based on this, the study sees the development of digital products as a so-called “supreme discipline,” distinguished by future and hybrid services.

This very hybrid idea should be considered as the guiding principle for the initial example. This is illustrated in the following cube:



MAGIC CUBE

The initial example is characterized by an extremely high degree of computerization. However, it also shows how much mathematical potential is possible within such a sensitive process. We want to permanently combine this important aspect with the concept of digitalization in the context of SMEs in a future-oriented and motivating way. According to [IW Consult, 2018](#) this process can be described by the following steps:

- Digitization;
- Digitalization;
- Datafication.

This process has been a repeated subject of discussion in the context of Industry 4.0 approaches and projects.

It is also about the virtual representation of processes and products as well as data-based business models. What is distinctive here is the autonomous concept of system.

“Less is more”—Importance of AI and Big Data should not to be overstated

The intervention of two people at the crucial points may have made it possible for Donald to accompany his nephews after all. We call these

people “Phantomias” and present these actions as a possible intelligent control tower.

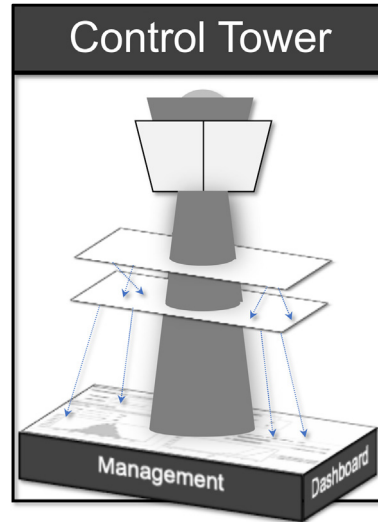


IMAGE CONTROL TOWER

Numerous SMEs have shunned digitalization because they cannot relate to abstract concepts like artificial intelligence and Big Data, or rather, they have been disappointed by promises, often exaggerated ones. This chapter aims to encourage the approach to this topic in a future-oriented way. The clock cannot be turned back. Digitalization is going to be one of the central and challenging core topics of the 21st century.

5.10 Maturity models

Within the scope of these digitalization efforts in SMEs, maturity models are of particular significance. How can the individual economic sectors be penetrated and developed harmoniously? How can different lines of development be assessed and how can interfaces be defined? It becomes clear that the focus will also be on further development and integration of individual technologies. The underlying study sees Germany only just at the start of this development. For SMEs this can be regarded as a special challenge.

- Digitalization is to be seen as a strategic challenge;
- Generating economic advantages by digitalization;
- Digitalization has to unfold within a pedagogical process.

Besides the control-tower concept, self-regulated learning is of particular importance within this process.

Flexible

Hybrid

CONTROLTOWER INTELLIGENCE

Agile

Sensor-based

In summary, it can be said that digitalization can only be successful when all six sides of the SME cube are coordinated and embedded in a complete overview.

ERP, RFID, and supply chain management must not be seen in isolation and independent of each other but are projected onto the individual sides of the cube. Big Data analyses are not an end in themselves but, as a connecting element, they aim at gaining deeper insights into the system.

5.11 Other success stories of mathematics and Industry 4.0

The main advantages of the combination of mathematics and Industry 4.0 are:

- The development of new business models;
- The creation of intelligent logistics and;
- The appearance of new strategies.

The following success stories should provide the reader with an overview of how impressive the combination of mathematics and Industry 4.0 could be.

5.12 General technological advantages

5.12.1 Cloud computing

Talks within companies are no longer about whether their applications are going to a cloud platform—the question is solely *how* they are going there.

The developments of cloud computing have made great strides in the past few years. The reasons for their fast deployment were the digital transformation and Industry 4.0.

With cloud computing companies saving investments in infrastructure, it is particularly suitable for introducing new IT systems which are especially

necessary when it comes to the implementation of Industry 4.0 within companies. Companies need new technologies for a smart factory. With the help of cloud computing, companies can slowly approach the smart factory process and start with subareas. Cloud solutions offer the opportunity to experiment and quickly come to solutions.

Companies like Siemens and Bosch are currently using cloud technologies for their IoT. With the help of cloud computing they are able to predict maintenance requirements of machine tools and to integrate drive systems. Predictive maintenance is the application which is used most often when it comes to cloud systems. In addition, another core area of the IoT cloud is to include all functions to connect devices, users, and companies with each other.

This example shows that cloud is one of the greatest success stories that has arisen out of Industry 4.0 and mathematics.

5.13 Success stories in companies

5.13.1 Bayer biopharmaceutical located in Garbagnate, Italy: the correct use of data

As the world economic forum discovered, most companies work with less than 1% of the data they generate. This means that more than 99% of data companies produce have no further use within the company itself.

However, at Bayer Biopharmaceutical this issue is very different. They try to get the most out of their own produced data. This has resulted in a 25% decrease in maintenance costs and a 30%–40% increase in operational efficiency. This makes Bayer Biopharmaceutical one of the leaders in the use of their own generated data.

5.13.2 Haier located in Qingdao, China: predicted maintenance needs

Haier is a Chinese industrial group and, since 2009, with a 5.1% market share worldwide, it has been a market leader in the area of household appliances. The company works a great deal with AI which has enabled them to create a “user-centric mass customization model” at the request of clients for their electronic products. The AI system they use is cloud based and is able to predict maintenance needs well before outage times arise. This puts Haier in an advantageous position because they have no issues regarding downtimes during the production process, which in turn optimizes their entire production time.

5.13.3 Phoenic contact located in Bad Pyrmont and Blomberg, Germany: digital twins

For their third biggest construction project, the electronic manufacturer Phoenic decided to rely on digital twins. This greatly reduced the company costs. In total, the use of the digital clones cut the maintenance costs and repairs by 30%.

As this example shows, coupling of the virtual and real worlds enables the analysis of data and the monitoring of systems to understand and process problems before they occur, avoiding downtimes, developing new opportunities, and planning for the future with the help of simulation.

5.13.4 Siemens located in Chengdu, China: augmented reality

Siemens uses 3D simulations to optimize its production lines. Their 3D system, called Simcenter 3D, offers a uniform, scalable, and expandable environment for 3D construction with simulation, testing, and data management. The system speeds up the simulation process based on well-developed geometry editing, the associative modeling of simulation, and combining cross-functional solutions. Simcenter is part of NX (which is discussed in more detail next) and fully integrated there.

By using augmented reality, Siemens has reduced the production time and increased efficiency by 300%. The integration of virtual and physical production systems leads Siemens closer to its optimal production process.

5.13.5 NX: a platform for the development of solutions

NX is a development platform with the approach of finding solutions for development, construction, simulation, and manufacturing problems. The toolset supports complex product complexity, while improving the performance and capacity of the entire product creation process. Finally, one of the outcomes is that the development times can be reduced by 30%. Due to its integrated data management, the automation of processes, support for decision-making, and other tools for optimization of the development process are interconnected. NX also promotes collaboration between the design and construction of the entire company. As a result, decisions within the company can be made more quickly and they can work more efficiently with their partners and suppliers.

5.13.6 Bosch Automotive in Wuxi, China

The most innovative manufacturing plant of this producer of auto parts and accessories has introduced a platform on which customers can continuously adapt their products. Additionally, due to the introduction of AI software running in the background, maintenance needs can be predicted in advance. This means that Bosch Automotive systems have the ability to predict the need for repairs or

services before they occur. Due to the implementation of radio-frequency identification-based tool management, the real-time analysis of machine data and inventory can be analyzed. Additionally, they also use data analytics, which helped the company to understand output losses and learn to eliminate them in the future.

The implementation of these emerging technologies enabled Bosch to have data connectivity, making it possible to react much faster and to be more agile within production. This has many advantages for Bosch Automotive, for example when it comes to changeovers, maintenance times, or breakdowns during the production process.

5.13.7 Summary

All of the various examples above are different. Nevertheless, they all have one thing in common: They are all participating in Industry 4.0 and are users of various mathematical applications and emerging technologies which make up a huge part of Industry 4.0. All these examples show that the mathematical aspects in the cyber-physical system are the most common thread in Industry 4.0.

5.14 Outlook: mathematics and Industry 4.0—digitalization and security

Mathematical technology is a key tool for Industry 4.0 and its importance will continue to grow.

Industry 4.0 provides the technical requirements, while mathematics brings the tools and raises the potential. The technical approach is very important, due to the fact that finally different components, for example, machines, should be able to interact and communicate autonomously.

Critics may claim the initial example is not suitable because it is partially a safety-critical area, however, while this fact is accepted, such a safety-critical dimension does not reduce the importance of the control tower, but actually reinforces it. Every SME would therefore be well advised to combine their digitization process with the integration of an interacting control tower; in fact, such a focus on a central intelligence would probably be even more suitable than naively storing it in a cloud.

5.14.1 Digitization and security

5.14.1.1 A new challenge for Mathematics 4.0

Mathematics is therefore understood as the basis tool within Industry 4.0. From Big Data, 3D printing, virtual and augmented reality, automation, robotics, to digital twins and more, all of these emerging technologies have their origins in mathematics.

The mathematical tool which prepares data in a way that finally enables decisions to be made from data is data science. Data science consists of mathematics statistics, computer science, and “specific knowledge” like engineering. Various parts of mathematics, including linear algebra, statistics, numerical analysis/scientific computing, mathematical computing, number theory probability, and logic and operations research influence data science. Mathematics is fundamental to data science because it represents a huge part of it.

When it comes to the preparation of data, there are several useful methods for the preparation process, for instance, data mining, data analysis, programming, AI, machine learning, and research.

From income inequality to climate change, technology will play a critical role in finding solutions to many of the challenges our world faces today. This year’s emerging technologies demonstrate the rapid pace of human innovation and offer a glimpse into what a sustainable, inclusive future will look like.

Jeremy Jurgens, Chief Technology Officer, *World Economic Forum*

In the final step, the aim is to set up structures so that a digital network is able to run on its own. This is why it is important to suggest that within a company the provision of a network and the availability of digitization alone are insufficient to create intelligence. The reasons for this include the fact that a digital network alone will generate no added value. For that reason, at this stage mathematics is highly required.

The various uses of data call also for a new approach to mathematics and another novel use of existing techniques. Therefore, a connection between current research and practice is important regarding the use of Industry 4.0 within various industries.

In the end, the aim is to identify structures within a system which can be recognized with the utilization of statistics and machine learning. Mathematical models and algorithms are fundamental, especially their hardware and software implementation play an important role when it comes to structure building. With the identification of structures and progress in mathematical optimization even complex problems can be solved.

Mathematics and computer science open up enormous opportunities for industrial innovation.

Regarding the future, the importance of mathematics will inevitably increase further within Industry 4.0. A perfect combination of higher mathematical tools and classic planning will enable the prerequisites for Industry 4.0 to be guaranteed.

We must develop a comprehensive and globally shared view of how technology is affecting our lives and reshaping our economic, social, cultural, and human environments. There has never been a time of greater promise, or greater peril.

Klaus Schwab, Founder and Executive Chairman, *World Economic Forum*

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Proposal and application of a framework to measure the degree of maturity in Quality 4.0: A multiple case study

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6.1 Introduction

From World War II to the present day, the world has been constantly readjusted on economic and political issues. The accelerated technological progress brought about by globalization causes structural and organizational changes. In this scenario, and in return for the rapid spread of knowledge in innovation and global competition, organizational boundaries have become more fluid and dynamic (Kurt, 2019).

For the purpose of competitive advantage, companies must satisfy their customers effectively and quickly (Calantone et al., 1995; Prahalad and Hamel, 1990). Consumers, in turn, are increasingly demanding due to the high variety of products available on the market and, therefore, quality has become relevant to organizations in order to differentiate their products. Product development, however, is a process of a complex chain of eventualities and decisions with the risk of being broken at any juncture that is most fragile (Kwon et al., 2014).

The development of the Fourth Industrial Revolution allowed a connection between the digital and physical worlds, integrating people, devices, and processes (Kagermann et al., 2013; Posada et al., 2015).

According to Klaus Schwab, founder of the World Economic Forum, the changes in this current revolution are so intense that they can be both promising and dangerous. The fear pointed out by the author refers to the fact that decision-makers will not be able to think strategically about the breakthrough forces and innovation that shape the future. Schwab (2017) claims the occurrence of a new transformation due to three reasons, encompassing (1) speed because it occurs at a very intense pace; (2) amplitude and depth, leading to a change in paradigms; and (3) the systemic impact, as it involves the transformation of countries, companies, and society.

Therefore, the transformations of organizational management, including the quality context, in the new concept of industry should be under careful observation by the leaders of companies, as the monitoring and improvement of processes are among the top topics covering Industry 4.0.

Quality 4.0 aligns quality management with Industry 4.0 to enable efficiency, performance, innovation, and new business models of companies. However, quality teams have little debate about action and change management to harmonize quality with the attributes, principles, and technologies of the digital era (Jacob, 2017).

Despite the notoriety that the Fourth Industrial Revolution has presented in recent years, the theme Quality 4.0 has not been greatly explored since there are still few works in the literature that propose to study and map the alignment of quality management with practices and technologies from Industry 4.0. Therefore this chapter presents the proposal and application of a framework for measuring quality maturity by companies operating within the scope of Industry 4.0, in order to understand if organizations have their respective quality departments following the progress generated by the implementation of Industry 4.0, contributing to a holistic approach to organizational management.

6.2 Industry 4.0: Pillars and perspectives of integration

According to Hermann et al. (2016), industrial revolutions manifest an abrupt and radical transformation, and these occur historically when science, technology, and new perceptions of the world bring about intense economic and social changes.

The sophistication and integration of digital technologies is opening the way for a new revolution that creates a world in which physical and virtual production systems cooperate globally and flexibly through intelligent factories, enabling producer customization and development of new operating models (Wang et al., 2016).

The concept of the Fourth Industrial Revolution was first used in 2011 at the Hannover Fair, when an initiative called “Industrie 4.0,” consisting of representatives of business, politics, and academia, promoted the idea as an approach to strengthen the competitiveness of the German manufacturing industry. In the same year, the Federal Government of Germany announced the use of Industry 4.0 as an integral part of its “High Tech Strategy 2020 for Germany” initiative, aiming at technology innovation leadership (Kagermann et al., 2013).

The Fourth Industrial Revolution is not just about smart tools and the connection between them, but encompasses the integration of technologies and the relationship between physical, digital, and biological domains. Moreover, the expected economic impact of this revolution is very high, as this new industry concept promises to increase operational efficiency as well as the development of every new business model, services, and products (Kagermann, 2015).

According to the literature review developed by Hermann et al. (2016), there are four key components for Industry 4.0, namely Cyber-Physical Systems (CPS), Internet of Things (IoT), Internet of Services (IoS), and Smart Factory.

Lee (2008) points out that CPS refer to integrations of computing with physical processes, so computers and integrated networks monitor and control these processes, usually with response rotations when connected. Three phases characterize the development of CPS and the first stage encompasses identification technologies such as radio frequency identification that allow a single identification. The second phase includes sensors and actuators with a limited range of functions. Finally, the third generation is equipped with many sensors and actuators, as well as being compatible with networks and can store and analyze data (Bauernhansl, 2014).

The IoT is a network in which CPS interact with each other through unique addressing schemes to achieve a common goal (Sony, 2018). According to Dombrowski et al. (2017), IoS enables multivendor value-added services to be offered and accessed through various Internet channels. This development enables a new way of dynamically varying the distribution of value chain activities.

Therefore, CPS, in the productive environment, integrate intelligent machines, digitally developed warehouse and production systems, and include end-to-end integration, from material input to distribution and service. IoT and IoS, in turn, enable networking by incorporating the manufacturing process, turning factories into a smart environment (Kagermann et al., 2013).

Smart factories self-contextualize and, consequently, help employees and machines in the execution of their activities, through the information captured from the physical and digital worlds (Lucke et al., 2008). They are considered the key to the implementation of Industry 4.0 (Kagermann, 2015).

Considering the perspectives of integration in Industry 4.0, the horizontal integration of value networks stands out, which aims to create collaborations between

companies, resulting in an efficient ecosystem in which material, data, energy, and finance can flow smoothly between different organizations. Also, all information on the current condition of the value chain will be available and can be used for better control of the flow of value (Kagermann et al., 2013; Wang et al., 2016).

In addition to business models and forms of cooperation between different companies, it is also necessary to address topics such as sustainability, protection of know-how, standardization strategies, and personnel development initiatives. Thus, organizational strategies, new network values and new business models will have their ecosystem supported and deployed using CPS (Sony, 2018).

Another form of interaction refers to the digital integration of engineering throughout the value chain. Besides being based on the other integrations, it aims to develop a software program chain that enables smart factories to predict the effects of product design during production, making it feasible to manufacture individual customer products (Wang et al., 2016).

Appropriate information technology (IT) systems should also be deployed to provide end-to-end support across the product value chain and across different companies, incorporating all customer requirements (Kagermann, 2015).

The third key aspect is vertical integration, that is, the development of a network manufacturing system that is flexible and reconfigurable through seamless integration of hierarchical systems within organizations (Stock and Seliger, 2016).

In fact, manufacturing structures will no longer be fixed and defined. An IT configuration set will be defined so that it can be used to support case by case to build a specific structure automatically for each situation, including all specific information, model, communication, and algorithm requirements (Kagermann et al., 2013).

6.3 Quality 4.0: Alignment of quality in the new scenario of the Fourth Industrial Revolution

Juran and Gryna (1993) explain that quality translates into aspects of product specifications that harmonize with customer requirements and thus ensures customer satisfaction. The concept of quality, as well as its dimensions, needs to be constantly adapted and updated, in line with changing consumer demands.

Currently, the quality of products, services, and processes is essential for achieving economic success and ensuring competitiveness (Müller, 2014). Quality management has become indispensable in organizations due to rising customer expectations, global competition, and the continued leverage of product complexity, and is therefore part of corporate objectives, strategies, and policies (Brüggemann and Bremer, 2012).

Quality 4.0 does not replace traditional quality methods but enhances them so that the new concept of quality goes beyond technology and embraces technology users and processes to maximize value. According to LNS Research in *Quality 4.0 Impact and Strategy Handbook*, Quality 4.0 is a reference to Industry 4.0,

being the digitization of quality management to encompass technology, processes, and people (Jacob, 2017).

Considering DIN ISO 9000, there are eight steps to developing, deploying, managing, and improving an existing quality management system. The first step is to determine the needs and expectations of customers and other stakeholders, and then, the stabilization of the quality policies and objectives of the organization. In the third step, the processes and responsibilities necessary to achieve the objectives listed in the previous step are defined. Subsequently, appropriate resources are defined and provided to ensure achievement of objectives. Methods for measuring the effectiveness of each process are then stipulated and applied. Sixth, means of preventing noncompliance and eliminating its causes are constituted. Finally, a process for continuous improvement of the quality management system is established and applied (Foidl and Felderer, 2016).

Industry 4.0, in turn, is represented by the three key aspects mentioned earlier in this chapter, that is, horizontal, vertical, and end-to-end engineering integration (Sony, 2018; Stock and Seliger, 2016). According to Foidl and Felderer (2016), the eight steps to implementing and improving the quality management system correspond to a way to connect Industry 4.0 and quality.

The Fourth Industrial Revolution is characterized by a huge range of aggregate data. Due to the possibility of combining and integrating information from different sources that was not previously possible, there are several possibilities for the quality management domain to use it. Processing and filtering them, however, in order to provide transparent and useful information to employees is a challenge to come (Elgendy and Elragal, 2016).

Based on the Industry 4.0 horizontal integration aspect, several new business models emerge. Customers, for example, can use services to track and monitor their orders in real time, enabling them to place their change requests at the last minute and will still be considered in production. In fact, focusing on the end-to-end engineering aspect, the CPS concept enables this methodology that covers all aspects of customer requirements down to product architecture and production. This is the manufacture of individual consumer products (Navickas et al., 2017).

Thus, the new industrial revolution has digitized operations and resulted in transformations in production efficiency, supply chain performance, product innovation, and complexity, as well as, in some cases, made entirely new business models available. From this organizational and productive environment perspective, Quality 4.0 must be inserted and acting to improve the culture, collaboration, competence, leadership, and processes of a company. Therefore, Quality 4.0 ensures alignment between quality management and Industry 4.0, so changes need to be carefully monitored by the organization leaders.

6.3.1 Quality 4.0 organizational dimensions

Inserted in the digital era and facing the advancement of Industry 4.0, which is one of the most discussed topics in the market and academia nowadays (Dombrowski

et al., 2017; Erol et al., 2016; Kagermann, 2015, Sony, 2018; Rajabion et al., 2019; Ruiz-Sarmiento et al., 2020; Tortorella et al., 2020), the organizational environment is characterized by complexity and volatility. Hence, companies need to manufacture products with ever higher quality at a sustainable cost and in order to meet the growing demands of their customers, demonstrating the need to rethink and invest in quality management to optimize indicators and ensure competitiveness (Foidl and Felderer, 2016).

According to LNS Research and SAS Institute (Jacob, 2017), the leader in analytics, Quality 4.0 can be assessed based on 11 dimensions, encompassing data, analytics, connectivity, collaboration, app development, scalability, management systems, compliance, culture, leadership, and competency.

6.3.1.1 Data

The large volume of data that the organization operates daily has become relevant to quality processes, so storage and exploration are strategic for optimizing actions. According to Cui et al. (2020), the amount of information used to achieve assertive results in more efficient decision-making and operations has grown exponentially in companies in recent times. Companies are already able to gather a wealth of data about the current state of their IT structure, which needs to be processed promptly and correctly to identify what information is relevant to business needs.

Given the large growth of data set, traditional management systems no longer have enough data-processing capacity in a tolerable time, so it fits into the concept of Big Data. Thus, requiring more advanced analysis tools and techniques, Big Data is linked with the diversity, distribution, and scale of data, being characterized by volume, variety, and speed (Elgendy and Elragal, 2016).

Big Data processing is generally intended for the extraction or discovery of large amounts of data, integrating various techniques from multiple disciplines such as statistics, machine learning, high-performance computing, pattern recognition, neural networking, data visualization, information retrieval, signal processing, and temporal data analysis (Miloslavskaya and Tolstoy, 2016).

Traditional systems have a large amount of transaction logs, but the data volume of connected devices is much larger, requiring special approaches like Data Lakes. In addition to data volume, variety and speed also differentiate a traditional IT system from more advanced approaches. Systems gather three types of data, that is, structured, unstructured, and semistructured. Structured data are highly organized; unstructured data are disorganized; finally, semistructured data are unstructured, but have a certain structure applied to them. Speed, in turn, matches the rate at which a company gathers data (Khine and Wang, 2017; Wang, 2017).

Conceptualized as a massively scalable repository for raw data storage, integration and exploration, Data Lake is broader than a data warehouse because it accepts unstructured and semistructured data and is based on lower cost technologies. Thus, the large volume of data can be stored in its original format in a central repository, eliminating the need for complex data preprocessing. It also enables different types

of analysis, from dashboards to real-time analytics, Big Data processing, and machine learning to guide decision-making (Giudice et al., 2019).

Still within the scope of Big Data, it is of great organizational interest to identify data that should be more urgently employed, that is, more time sensitive. Therefore, there is Fast Data which is based on fast data extraction so that action can be taken to solve a problem (Miloslavskaya and Tolstoy, 2016).

6.3.1.2 Analytics

Business analytics approaches aim to generate competitiveness for the organization, besides collaborating in the decision-making process. From the perspective of exploring different data sources and adopting a customer-centric approach to quality, analytics is increasingly generating value for the organization to help optimize the entire value chain (Elgendy and Elragal, 2016).

Conceptually, analytics makes use of the application of different mathematical, statistical, predictive modeling, and machine learning techniques to identify correlations and patterns, generating advantages for the company through a better understanding of the business environment (Kibria et al., 2018).

In fact, Big Data analytics encompasses process, techniques (e.g., analytical methods), and tools (e.g., data-mining tools) used to generate meaning and actionable insight from a large volume of data (Kwon et al., 2014).

The importance of developing data analytics capabilities by companies is growing, so that organizations must develop capacity to generate insights aligned with the organization's strategy from data analysis and management (Mikalef et al., 2018).

There are currently three predominant types of analytics in use (descriptive, predictive, and prescriptive) to collaborate with decision-making at the strategic and operational level. In order to guide future actions based on data collection, descriptive analysis generates information about past or current events, mainly using performance indicators to describe organizational panoramas that are commonly spelled out in reports. Predictive analysis predicts the proposition of scenarios based on data analysis, enabling planned decision making in anticipation of probable events. Finally, based on predicted scenarios, prescriptive analysis drives more assertive action by developing time series data trends and correlations, applying advanced statistics, data mining, and high computational power to generate real-time responses (Kibria et al., 2018).

Therefore, prescriptive analysis is more advanced, it predicts failure and specifies what must be done to resolve or change the result, and usually includes some level of unattended behavior. Traditional views include reports, graphs, and dashboards, while Big Data views include mashup apps (a combination of two apps that can complement and enhance a given service offering) (Jacob, 2017).

6.3.1.3 Connectivity

Faced with the digital era and Industry 4.0, connectivity gains relevance, allowing the association and interaction between organizations, people, products, processes,

and devices, in order to result in increasingly complex, diverse, mobile, and high-magnitude networks (Dalenogare et al., 2018; Verhoef et al., 2017).

Therefore, from the fluid boundary between the digital and physical world, there is the connection of different technologies, including IT directed to the business area [e.g., product lifecycle management and enterprise quality management system (EQMS)], and technologies directed to the operation area, applied in the manufacturing sector (Jacob, 2017).

This new scenario generates the need for companies to develop strong and deep connections throughout the value chain to connect suppliers, customers, employees, and objects (machines), incurring supply chain agility to adapt briefly to new customer demands, reduce failures and rework, increase productivity, and optimize device reliability (Verhoef et al., 2016).

Connected products will enable real-time failure, performance, and lifecycle collection. Connected devices will enable operating systems to be optimized through predictive and prescriptive decisions based on the transmission of a large amount of data. Connected processes, in turn, will generate data about products and devices that will feedback routes (Kwon et al., 2014).

In addition to connected supply chain, connected products, connected processes, and connected devices, it is important to connect employees, developing an ecosystem based on connectivity, interaction, and strategic alignment. Thus, connected workers making use of the company's personal or portable devices will incur performance gains and safety at work, impacting productivity (Jacob, 2017).

6.3.1.4 Collaboration

Increasing complexity of products, processes, and technologies has led to collaborative problem-solving, making collaboration in the industrial context increasingly relevant to improve productivity.

Especially in terms of quality, given its transverse characteristics and the need for engagement of all workers at different levels of the organization, collaboration should be present. Herter and Ovtcharova (2016) further state that collaboration, given the Industry 4.0 scenario, will be highly impacted by connectivity, data, and analytics, leveraging the company's innovation indices and optimizing continuous improvement practices.

Deploying an EQMS system can help significantly improve manufactured products. Using EQMS, as a support for connecting various enterprise software systems for quality, can enhance collaboration with internal and external stakeholders, and enable real-time and secure access to quality data and manufacturing. EQMS works with a company's ERP to form a digital record. Combined, they manage the business processes needed to make a quality product. Also, visibility in costs enables greater control of internal processes as well as supply chain efforts (Jacob, 2017).

Through knowledge exchange, negotiation, and collective decision-making, collaboration can occur even by making use of social media, helping to promote a quality culture (Li et al., 2018).

Blockchain is another technology that stands out in the context of quality, mainly with regard to the supply chain, and is characterized by traceability, trust machine, and decentralized governance. Therefore, blockchain technology can be applied to product lifecycle tracking and promises to increase confidence in supply chain quality management (Chen et al., 2017).

6.3.1.5 App development

Efforts are currently being made to develop automatic control systems or products to reduce human interference and enable remote control of processes based on rules and standards. Commonly, these control processes are operated through PC software, limiting the mobility and agility of provisions. Thus, the need arises for mobile applications that can achieve the same goal as a PC but optimizing the mobility and speed of decision-making (Yan et al., 2017).

It is also noteworthy that the development of apps becomes important in order to facilitate industrial processes, as the employee is increasingly used to using apps in their daily lives, being represented by the growing number of smartphone sales.

The use of apps becomes a viable and practical mechanism for process control, data collection, data exposure, analysis visualization, connection, and collaboration, without physical or temporal restrictions. In fact, in the context of a smart factory, automation and intelligence will increasingly stand out, exploring the combination of mobile applications in the industrial sector (Shu et al., 2016).

Therefore, value for mobility, with no time or place limitation, will drive the development and use of interactive applications for quality management, so that wearable growth can be cited to optimize industry safety and performance, as well as augmented reality, which assists in different ways the operation through integration of the virtual into the real world, and virtual reality, which provides the simulation of real events, generating value for process management (Jacob, 2017; Jacobs et al., 2019).

6.3.1.6 Scalability

From a global-scale perspective, scalability refers to the ability to support devices, data, people, and analytics. It is noteworthy that unless considering a global-scale view, quality in line with Industry 4.0 will not achieve the integration and convergence of lessons learned, competencies, process design, and best practices across the organization (Jacob, 2017).

According Khan et al. (2017), Big Data, in terms of architecture and tools, collaborated to scale analytics solutions for quality development. Also, cloud computing is a major contributor to scalability. Unlike local solutions that make sharing difficult and difficult to scale, cloud computing focuses on data sharing and computing resources on scalable networks, facilitating lower cost processing and storage based on immediate availability.

Cloud service models include Software as a Service (SaaS), Platform as a Service (PaaS), and Infrastructure as a Service (IaaS). SaaS enables access to

cloud-based software, so applications can be allocated across a remote network, enabling joint data analysis and project collaboration. PaaS refers to a cloud platform that equates to an environment for application development, customization, management, and testing. IaaS refers to a cloud service that is related to a computing infrastructure, such as hosting the site or even Big Data analytics, making use of storage, servers, and other resources available on the network (Singh and Malhotra, 2012).

6.3.1.7 Management system

Nowadays, the organizational environment is based on digitization, so that companies need to make technological changes to their practices, processes, and management systems to stay competitive (da Costa et al., 2019). Thus, proper quality management, based on Industry 4.0-oriented processes and technologies, facilitates product development, reduces cost of failures and rework, and increases the high degree of customer satisfaction (Foidl and Felderer, 2016).

Within Industry 4.0-aligned quality management systems, EQMS stands out for providing a scalable solution aimed at automating work activities, connected quality processes, increasing compliance, and promoting a collaborative digital environment. EQMS should be adopted by the organization in an integrated manner with other management systems, as quality affects the entire value chain of the company, requiring holistic management and vision (Jacob, 2017).

Therefore, based on the conception of connected users, processes, and objects, technological solutions designed to manage the increased complexity of quality regarding planning, control, and monitoring will be necessary, improving practices and optimizing the results of the organization.

6.3.1.8 Compliance

Comprising conforming to manufacturing, customer, regulation, and internal aspects, compliance activities gain notoriety over prerequisites toward Industry 4.0 to enable flexible and customized production based on new technologies.

In fact, as technologies for Industry 4.0 are implemented and operationalized in the industrial sector, including artificial intelligence, augmented reality, autonomous robots, among others, the organizational environment is significantly changed, including compliance obligations (Terzimehic et al., 2017).

In the area of quality, meeting compliance requirements is essential to ensure that processes, products, and services comply with specifications (Jacob, 2017).

Currently, there are compliance technologies that aim to extract high value from data, assist in decision-making, and facilitate processes for compliance employees. Thus, in the face of the Industry 4.0 scenario, the quality department has the chance to apply automated compliance, even allowing the sharing of successful practices and lessons learned. In order to avoid data fluctuations, analytics can be applied. In addition, compliance management can be incorporated into automated compliance auditing, leading to cost and error reductions as well as risk management optimization (Dimyadi and Amor, 2017).

6.3.1.9 Culture

The Fourth Industrial Revolution is transforming from organizational processes to working conditions, impacting the culture of companies. Nowadays, organizational culture assumes a relevant role in the implementation of Industry 4.0 in order to support the new strategies and objectives of a company (Hecklau et al., 2016).

Especially in the quality area, there is a need to engage all hierarchical levels with the culture of quality to promote organizational and production changes in accordance with the new customer requirements. Therefore, understanding the need for quality to be aligned with Industry 4.0, working with real-time data, collaborative environment, connectivity, transparency, and focus on continuous improvement, becomes a strategic factor for the organization's competitiveness (Mohelska and Sokolova, 2018).

Data sharing and apps development, as well as the connection of processes, people, and devices, bring a new perspective for quality culture in the context of the digital era (Jacob, 2017).

6.3.1.10 Leadership

Due to the changes generated by Industry 4.0, reflecting on management approaches and practices is of great value to contribute to the successful implementation and operationalization of this new concept (Mihardjo et al., 2019).

Promoting engagement and collaboration, as well as the development of new skills, needs to be the focus of leadership, considering a social, digital, and technological perspective.

Leadership that acts directly in the quality sector must pay attention to the company's strategic objectives and value actions that support these goals, following the changes generated by the Fourth Industrial Revolution using new technologies, tools, processes, and data in real time (Jacob, 2017).

Therefore, ensuring that the quality department progresses in a manner compatible with the implementation of Industry 4.0 is necessary to adapt the organization to this new paradigm, as well as assisting in a holistic vision of digitization of the company, starting from metric-based monitoring (Mohelska and Sokolova, 2018).

6.3.1.11 Competence

The development of new competences is necessary in order to consider the use of new technologies, digitization of processes, scale customization, large data volume, and the collaborative and connected environment (Akkari et al., 2019; Reuter et al., 2017; Roldán et al., 2019).

Faced with increasing complexity in the productive sector, the generation of new knowledge, attitudes, and skills will allow leverage of the workforce performance in a context of changes and adaptations (Hecklau et al., 2016).

Since the quality area plays a central role in a smart factory, a strategic approach that provides for the periodic qualification of employees and the application of a learning management system will create a competitive advantage for the organization.

6.4 Framework development to assess the organization's Quality 4.0 maturity

The framework development was based on three steps according to [Schumacher et al. \(2016\)](#). Initially, a strong literature review was developed to allow a broad understanding of the subject. Therefore the pillars, attributes, and technologies of Industry 4.0, as well as different quality management philosophies and the organizational dimensions potentially impacted by the implementation of Industry 4.0 regarding quality were studied.

Based on this exploratory study, this was followed by the framework design and structuring focusing on the objective of companies' maturity degree evaluation in Quality 4.0. In this phase, the maturity analysis parameters were modeled, as well as the maturity levels for Quality 4.0.

Finally, in order to evaluate the framework as a practical tool for use, the instrument was applied to two multinational companies, as explained in Section 6.5.

Therefore, in order to identify the organization's degree of maturity in Quality 4.0, the framework considered 11 organizational dimensions proposed by the LNS Research and SAS Institute ([Jacob, 2017](#)).

Each of the different perspectives associated with Quality 4.0 was approached from two parameters, resulting in two closed questions for each dimension from use of the phrase completion scale to enable an objective data analysis. This scale has a continuous score from 0 to 10, with complementary sentences and a single statement, where 0 is associated with the absence of the attribute and 10 is associated with the maximum intensity of the presence of the attribute. In this structure, ordinals 0, 1, and 2 relate to the inexistence or very low existence of the attribute; 3 to 7 show limited existence of the attribute; and ordinals from 8 to 10 demonstrate the presence of the attribute ([Hodge and Gillespie, 2007](#)).

[Figs. 6.1–6.3](#) present the proposed instrument considering the different dimensions and [Fig. 6.4](#) shows the two parameters considered for the evaluation of each dimension.

Also, the instrument was submitted to a pretest with researchers and market professionals who had affinity with quality and the Fourth Industrial Revolution aiming at achieving the efficiency of time and assertiveness in the data collection performed in the organizations.

The framework conceives five evolution degrees for Quality 4.0 maturity ([Fig. 6.4](#)), as follows:

- Absent quality—from 0% to 19.99%: without knowledge about quality management, the company does not apply and does not plan the practice of quality.
- Basic quality—from 20.00% to 39.99%: the company has a basic knowledge of traditional quality management but is not aware of new practices, technologies, systems, and tools applicable to the quality area.
- Traditional quality—from 40.00% to 59.99%: the company has a basic knowledge about Quality 4.0. In this graduation, the result suggests that the

Dimension	Pharase completion scale										
Data	0	1	2	3	4	5	6	7	8	9	10
Information of different natures of the company...	...are not available in a common data storage model.			...are available in a common data storage model, but with restricted access depending on their nature.					...are available in a advanced data storage model and everyone in the organization has access to them.		
Company information update...	...is very slow, making them obsolete when available on the system.			...is performed periodically.					...is performed in real time		
Analytics											
Data analysis in the company...	...is very slow and periodic, performed manually by a responsible worker			...is performed quite often by computers that trigger data entered into the system by a worker.					...is performed in real time through big data analytics.		
Data analysis in the company...	...only descriptive, monitoring of known correlations.			... is predicted and uses statistical programs to predict scenarios, enebling planned decision making.					...prescriptive. Artificial intelligence/machine learning predicts the failure and proposes solution to the problem.		
Connectivity											
Employee connectivity in the company...	...does not exist, because smart devices are not used by the company.			...is controlled as only the highest hierarchical positions can enjoy smart devices.					...is widespread, since all individuals in the company use smart devices to work.		
Feedback rom company's products is conducted...	...through questionanaires applied to customers periodically and which are analyzed and computed manually.			...through frequent customer satisfaction surveys, available online and computationally analyzed.					...through the own product that is connected to the system, providing real time feedback about its performance throughout its life cycle.		
Collaboration											
Blockchain...	...is not a company investment plan.			...is a future investment plan for the company to review characteristics or attributes that must be tested at supply chain levels to provide traceability throughout the product life cycle.					...it is already a company practice.		
Enterprise quality management software (EQMS)...	...is not a company investment plan.			...It is a future investment plan for the company to provide a scalable solution aimed at automating work activities and promoting a collaborative digital environment					...it is already a company practice.		

FIGURE 6.1

Part I of the proposed instrument to evaluate the degree of maturity in Quality 4.0, considering data, analytics, connectivity, and collaboration dimensions.

Authors (2018).

Dimension	Pharase completion scale										
App development	0	1	2	3	4	5	6	7	8	9	10
The company...	...does not invest in mobile applications in the industrial sector.			...periodically invests in mobile applications in the industrial sector.					...invest in mobile applications through multiple interfaces divided by functions and the interaction between them (mushups).		
Wearable devices that generate and transmit employee data...	...was never commented as an investment in the company.			...It is a company future investment plan.					...It is already a reality in the company to ensure productivity and safety.		
Scalability											
Volume of data, devices and analytics...	...is stored in unshared folders.			...It is stored on networks that are not connected on a global scale.					...is stored in global accessibility and high availability networks		
Cloud computing...	...is not a practice in the organization.			...is used quite often depending on the confidentiality of the data.					...is used in the company for all typed of data.		
Management systems											
Quality management in the organization...	... is traditional, in which the defects are tracked, and supervisors inform to employees what to do based on the organization's short-term goals and objectives.			...is based on TQM, in which quality goes beyond customer needs and expectations and is committed to all hierarchical levels of the company.					Performed through an advanced software, enable real-time and secure access to quality data.		
Enterprise quality management swtare (EQMS) deploying...	...it is not a company investment plan			...is a company investment plan to automate workflows, connect quality processess, improve data accuracy, provide centralized analytics, and ensure compliance.					...is already a company practice and is adopted in an integrated manner with other management systems.		

FIGURE 6.2

Part II of the proposed instrument to evaluate the degree of maturity in Quality 4.0, considering app development, scalability, and management systems dimensions.

Authors (2018).

organization has some knowledge about quality management in the new concept of Industry 4.0. However, the organization does not plan a short-term investment in order to foment quality alignment with Industry 4.0.

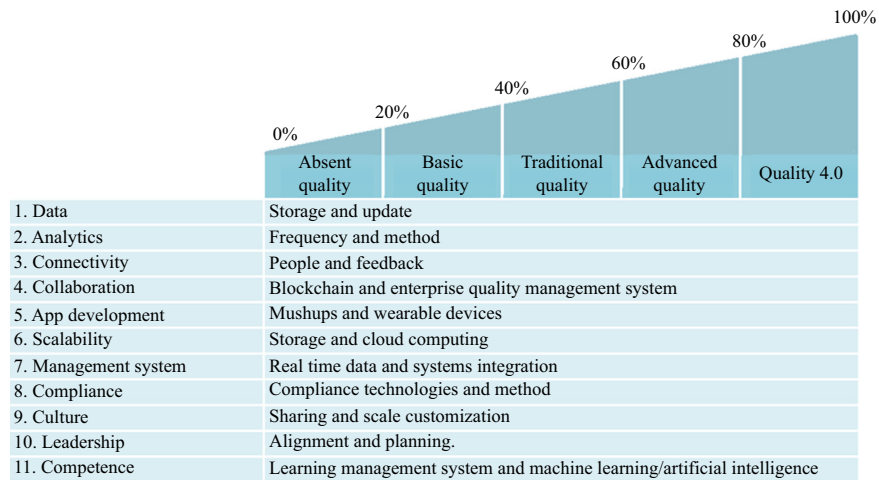
- Advanced quality—from 60.00% to 79.99%: the company has an average knowledge of Quality 4.0, suggesting that although the company still does not practice Quality 4.0, the organization is already planning to use technologies,

Dimension	Scale										
Compliance	0	1	2	3	4	5	6	7	8	9	10
In the company...	...common processess are performed manually by employees.			...the preconfiguration and automation scope of common processes exist to reduce the effort required to perform performance qualification.					...compliance technologies exist to extract high value from data, and success and failure approaches are shared between times in real time through industry 4.0 mechanisms		
Regarding compliance...	...the company does not value applying a set of disciplines in order to accomplish established legal and regulatory requirements, policies and guidelines.			...the company values inclusion in its culture in order to all employees to practice and manage if it is being applied.					...not only does the company value compliance as part of its culture, it also focuses on improving its control through technologies 4.0.		
Culture											
Quality culture in the company...	... is undocumented and nto fully known by employees.			...although it exists, it is unknown to anyone who is not part of the quality department					...is achievable through the connectivity of data, processes and analysis, being shared by all employees of the company.		
Quality culture in the company...	...does not provide for scale customization, business transparency and error reduction			...predict the scale customization, business transparency and error reduction.					...applies scalability customization, business transparency and error reduction, encouraging the use of digital technologies for real-time performance monitoring.		
Leadership											
Quality culture in the company...	...is not following the transition to the industry 4.0 paradigm, so that a new technology tool or process has not been deployed.			...is following the transition to the industry 4.0 as it is deployed in the company through new technologies, tools or processes.					...is already aligned and prepared to support, reinforce and improve industry 4.0 results even before its fully deployed, using new technologies, tools or processes.		
Company leaders plan quality improvement...	...by applying basic quality tools.			... by improving the application od basic and advanced quality tools.					...by applying technologies 4.0 to manage data in real time.		
Competence											
The company...	...does not have a learnig managenet system for employees, being precarious investment in training.			...has a learning management system for its employees.					...has a learning management system through structured training throughout the company, coupling digital simulation to improve the delivery of results.		
The company...	...does not invest in developing new knowledge for employees.			...develops new knowledge through training and workshops with experts.					...develops new knowledge through machine learning/ artificial intelligence and leverages applications to improve employee competences.		

FIGURE 6.3

Part III of the proposed instrument to evaluate the degree of maturity in Quality 4.0, considering compliance, culture, leadership, and competence dimensions.

Authors (2018).

**FIGURE 6.4**

Quality 4.0 maturity degree, according to 11 organizational dimensions and two evaluation parameters for each dimension.

Authors (2018).

tools, and processes that will enhance the degree of alignment between quality and Industry 4.0.

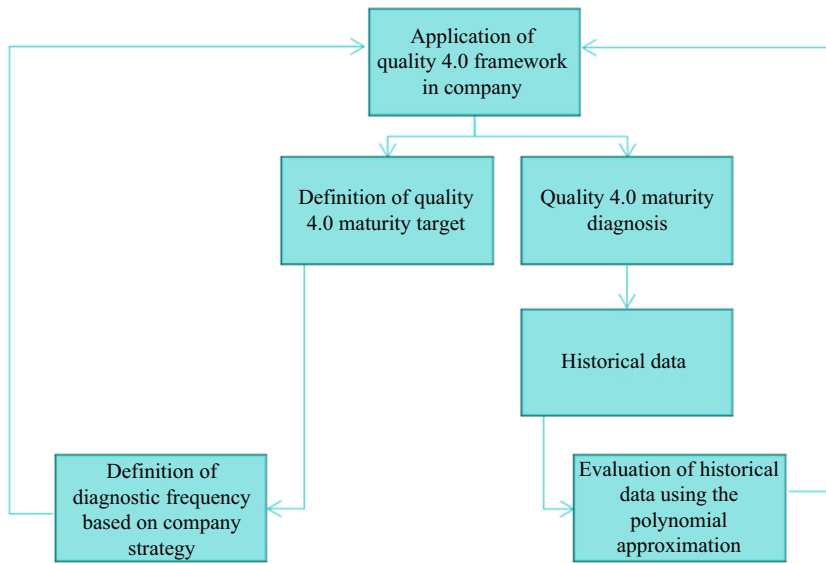
- **Quality 4.0—from 80.00% to 100%:** the company has an advanced knowledge of Quality 4.0, implying that the organization not only has an evolved understanding of it, but already uses technologies, tools, and processes that allow the alignment between quality and Industry 4.0.

As part of the framework, demographic questions were proposed to characterize the organization, identifying (1) the type of company; (2) the company's business sector; (3) the size of the company; (4) the location of the company; (5) the time of operation in the market; (6) the area of activity of the respondent; and (7) the respondent's time in the company.

The framework assumes the application of the instrument to at least three leaders directly linked to the quality department of the organization to avoid a unilateral view on quality management.

6.4.1 Systematic application and data treatment based on a numerical approach

In order to facilitate the change management process toward Quality 4.0 in companies, a systematic application and treatment of data obtained from the framework (Fig. 6.5) was defined, collaborating for the use of the instrument to drive quality practices aligned with Industry 4.0.

**FIGURE 6.5**

Proposal for a systematic application of the Quality 4.0 framework in companies.

Authors (2018).

The systematic application of the framework in organizations is based on historical data analysis to periodically evaluate the degree of alignment between quality and Industry 4.0 according to each Quality 4.0 dimension. It is proposed that the company establish a Quality 4.0 maturity goal to be achieved, considering the organizational strategy and the five degrees of evolution defined by the framework. Considering the goal definition according to the strategic planning of the organization, the company follows the definition of the periodicity of the diagnosis, that is, the organization needs to perform a programmed application of the instrument in order to monitor the evolution of maturity in Quality 4.0 according to each of the dimensions, analyzing potentialities and weaknesses.

From the diagnostics performed, based on the defined periodicity, the company will have a collection of historical data that indicates the degree of alignment between the quality department and Industry 4.0. Finally, the evaluation of historical data can be aimed at analyzing the evolution of Quality 4.0, as well as using a numerical method to extrapolate and obtain predictions about the estimated time needed to reach the maturity target set by the organization.

Also, numerical analyses can be performed to predict scenarios and make comparisons with other companies. In the predictions, a polynomial approximation using the least squares method is suggested, so that the function (Eq. 6.1):

$$y = f(x) \in E \quad (6.1)$$

is approximated by a polynomial of degree m (Eq. 6.2)

$$P_m(x) = F(x) \in E \quad (6.2)$$

According to Eqs. (6.3)–(6.8), in the discrete case, the function $F(x)$ is not known, being represented by pairs of points of the collected data. Being $n + 1$ pairs of points $(x_0, y_0), (x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$, where $y_i = f(x_i)$, $i = 0, 1, \dots, n$, with $n + 1$ distinct points, Eq. (6.2) can be represented by Eq. (6.3):

$$P_m(x) = a_0 + a_1x + \dots + a_mx^m \quad (6.3)$$

With maximum degree m , where $m < n$ (Eq. 6.4) it is minimal:

$$Q = \|f - P_m\|^2 \quad (6.4)$$

Considering that $m < n$, the linear product can be used (Eq. 6.5):

$$(f, g) = \sum_{k=0}^n f(x_k)g(x_k) \quad (6.5)$$

From Eq. (6.5):

$$Q = \sum_{k=0}^n \left(y_k - (a_0 + a_1x_k + \dots + a_mx_k^m) \right)^2 \quad (6.6)$$

Eq. (6.5) can be simplified as shown in Eq. (6.7):

$$y = Aa \quad (6.7)$$

where A is a Vandermonde matrix, as shown below:

$$A = \begin{pmatrix} 1 & x_0 & x_0^2 & \dots & x_0^m \\ 1 & x_1 & x_1^2 & \dots & x_1^m \\ \dots & \dots & \dots & \dots & \dots \\ 1 & x_m & x_m^2 & \dots & x_m^m \\ \dots & \dots & \dots & \dots & \dots \\ 1 & x_n & x_n^2 & \dots & x_n^m \end{pmatrix}$$

It is possible to know the coefficients through the inverse matrix of A from Eq. (6.8):

$$A^{-1}y = a \quad (6.8)$$

The polynomial equation (Eq. 6.3) can be written using the coefficient a , allowing the development of interpolations and extrapolations.

6.5 Quality 4.0: Multiple case study

Based on the proposal of Quality 4.0 framework, a multiple case study was conducted, approaching two large companies from the state of São Paulo (Brazil)

that already apply Industry 4.0 practices in their production lines, and it is interesting to explore their knowledge about Quality 4.0 as well as the current applicability of quality management in this new industry concept.

The first company studied is a German multinational company from the automotive sector that employing over 400,500 workers worldwide. The second company is also a German and centenary multinational company that operates in the energy sector and employs around 370,000 people worldwide.

The instrument was printed and applied on site to three quality department leaders from each company in order to get a holistic view of the quality area. Once answered, the questionnaires were collected, and the data were analyzed using Microsoft Excel.

In order to evaluate the internal consistency of the instrument, Cronbach's alpha coefficient was obtained (Eq. 6.9) to verify the stability and reliability of the instrument developed. This is a widely used coefficient, with a response range from 0 to 1 representing internal consistency.

$$\alpha = \frac{K}{(K-1)} \left[1 - \frac{\sum_{i=1}^k S_i^2}{S_{soma}^2} \right] \quad (6.9)$$

α = Cronbach's alpha; K = number of instrument items; S_i^2 = variance of each item; S_{soma}^2 = total variance.

Table 6.1 presents the variance of each item, so that the total presented is represented by the dividend in Eq. (6.9). The total variance, represented by the divisor in Eq. (6.9), is presented in Table 6.2, by which it is possible to calculate Cronbach's alpha coefficient.

The Cronbach's alpha coefficient result was 0.84 for the 22 questions elaborated, which indicates that the developed instrument presented reliability in the case study, because coefficients above 0.8 can be considered reliable (Streiner, 2003; Tavakol and Dennick, 2011).

6.5.1 Quality 4.0 maturity in the automotive industry

The quality leaders of the first company, which is a large automotive industry, have been working at it for over 10 years. Table 6.3 indicates the average of the answers to the two questions from each of the dimensions studied, as well as the average of each question per dimension and the organization maturity degree regarding Quality 4.0.

In the data indicator, which is the first dimension under study, the automotive company scored a Quality 4.0 maturity level of 71.67%. On this dimension, it was analyzed that there was different nature information for the company available in a common data storage model, but they have restricted access depending on its nature. Furthermore, the company's information is updated periodically.

Table 6.1 Variance of each item for the basis of the calculation to obtain Cronbach's alpha for the proposed instrument.

Question	Variance
Q1 data	5.86
Q2 data	2.70
Q1 analytics	0.66
Q2 analytics	1.36
Q1 connectivity	6.16
Q2 connectivity	2.30
Q1 collaboration	9.36
Q2 collaboration	0.66
Q1 app development	6.70
Q2 app development	11.86
Q1 scalability	4.56
Q2 scalability	7.46
Q1 management systems	6.30
Q2 management systems	5.76
Q1 compliance	5.46
Q2 compliance	1.86
Q1 culture	0.70
Q2 culture	2.66
Q1 leadership	1.6
Q2 leadership	2.26
Q1 competence	6.96
Q2 competence	4.26
Total	97.56

Authors, based on collected data (2018).

Table 6.2 Total variance for the calculation basis to obtain Cronbach's alpha for the proposed instrument.

Respondent	Total variance
1	15.04
2	51.04
3	84.37
4	145.04
5	26.04
6	165.37
Total	486.91

Authors, based on collected data (2018).

Table 6.3 Analysis of automotive industry results, highlighting the average of each question ($\overline{Q1}$) and ($\overline{Q2}$), the average of each dimension ($\overline{D}$), the maturity degree of each dimension (MD), and the final maturity degree in Quality 4.0 (MDfinal).

Dimension	$\overline{Q1}$	$\overline{Q2}$	$\overline{D}$	MD (%)
Data	6.67	7.67	7.17	71.67
Analytics	6.67	5.67	6.17	61.67
Connectivity	4.00	6.00	5.00	50.00
Collaboration	4.33	8.00	6.17	61.67
App development	7.00	5.33	6.17	61.67
Scalability	7.33	4.33	5.83	58.33
Management systems	8.67	5.67	7.17	71.67
Compliance	4.33	8.33	6.33	63.33
Culture	9.00	8.00	8.50	85.00
Leadership	6.00	6.33	6.17	61.67
Competence	9.67	7.33	8.50	85.00
MDfinal				62.12

Authors, based on collected data (2018).

On the other hand, in the analytics dimension, it was observed that data analysis in the company is performed with some frequency with the help of devices that compute the data digitized by an employee and that part of the application of descriptive and predictive analysis.

Connectivity in the automotive organization is restricted, since only the highest hierarchical position can use smart devices, and the company's product feedback is conducted through frequently available online customer satisfaction surveys which are automatically computed. This dimension got the lowest maturity degree related to Quality 4.0 among all 11 studied, corresponding to 50.00%.

As for collaboration, the company presented 61.67% of advance in this study's proposed scale for the Quality 4.0, so that blockchain is a future investment plan of the company in order to communicate about characteristics or attributes that must be tested at different supply chain levels as well as to provide traceability throughout the product life cycle.

According to respondents, with a score average of 6.17 for app development, the organization periodically invests in web-based apps, and wearable devices is a future investment plan for the company.

In the scalability concept, it was identified that data, devices, and analysis volumes are not stored in global accessibility networks at the automotive industry, and that the cloud storage is frequently used, depending on its data confidentiality degree, suggesting that the company does not practice the concept of Quality 4.0 in this index as a whole, corroborating as the second-lowest maturity result (58.33%).

Analyzing the management systems, EQMS is an organization's investment plan in order to automate workflows, to connect quality processes, to improve the accuracy, and to ensure compliance. For this indicator, the degree of advancement in the scale developed in this work was 71.67%.

About the compliance, it is very usual the preconfiguration and automation scope for common processes at the organization in order to reduce the required effort to execute performance qualification. Also, the company not only appreciates compliance as part of its culture, but also focuses on improving its control through Industry 4.0 technologies.

The company's culture, in turn, proved to be one of the quality indicators that most closely accompanies migration to support the implementation of Industry 4.0 (85%). It was observed that this dimension is achieved through the data, processes, and analysis connectivity, which are shared by all the company's employees. In this way, scale customization, business transparency, and error reduction are achieved, which encourages the use of digital technologies for real-time performance monitoring.

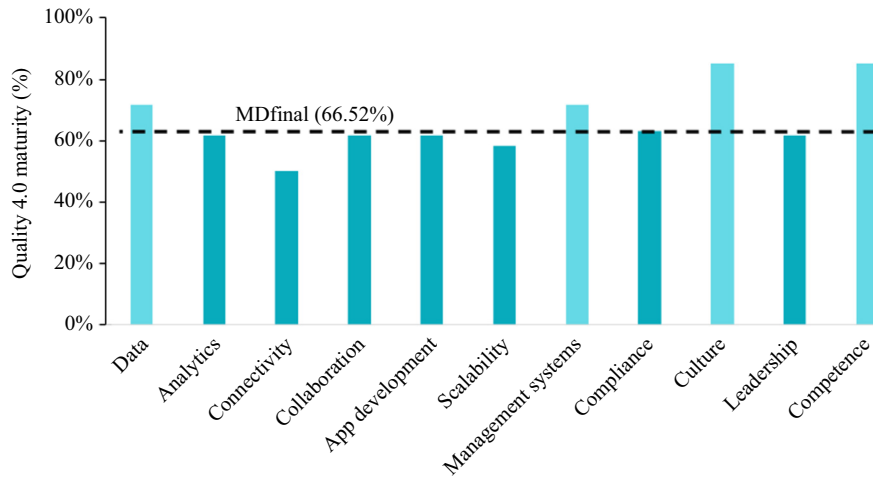
With regard to leadership, it was interpreted that the company's quality departments are in pace with the transition to the Fourth Industrial Revolution through new technologies, tools, or processes. However, in practice, the company leaders still plan current quality improvement by improving the application of basic and advanced quality tools.

In the competence indicator, together with the culture one, the organization reached the highest maturity degree in comparison with the other dimensions, scoring 85.00%. According to the respondents, the automotive company has a learning management process through structured training throughout the entire company, which indicates Quality 4.0 applicability in the competence dimension. By contrast, the industry has not developed new knowledge by machine learning or artificial intelligence yet, neither has it taken advantage of applications to improve employee knowledge so far.

Therefore, the dimensions that indicate Quality 4.0 practices were culture and the leadership, with both scoring 85% regarding the maturity degree related to the new quality management concept.

Fig. 6.6 illustrates the maturity degree obtained for each Quality 4.0 dimension by the automotive company, as well as its final maturity degree in Quality 4.0, inferring about the potentialities and weaknesses presented by the organization. The maturity of the automotive industry has reached a score of 66.52%, demonstrating that the organization is beginning the advanced quality stage, so that greater alignment between the quality department and Industry 4.0 is being planned.

Most dimensions achieved advanced quality, indicating that even though the company does not practice Quality 4.0 yet, it already has an advanced knowledge of its concept, and the organization has already made plans for implementing new technologies, processes, or devices in the short–medium term. On the other hand, with a lower maturity degree, the dimensions connectivity and scalability stand out, with indexes close to 50%, which suggests that the company still has a few weaknesses regarding Quality 4.0.

**FIGURE 6.6**

Maturity degree for each dimension and final maturity degree (MDfinal) obtained in Quality 4.0 for the automotive company.

Authors, based on collected data (2018).

Table 6.4 Analysis of automotive industry results, highlighting the average of each question ($\overline{Q1}$) and ($\overline{Q2}$), the average of each dimension ($\overline{D}$), the maturity degree of each dimension (MD), and the final maturity degree in Quality 4.0 (MDfinal).

Dimension	$\overline{Q1}$	$\overline{Q2}$	$\overline{D}$	MD (%)
Data	8.00	5.33	6.67	66.67
Analytics	6.67	6.00	6.33	63.33
Connectivity	6.33	7.00	6.67	66.67
Collaboration	0.00	7.33	3.67	36.67
App development	8.00	1.33	4.67	46.67
Scalability	7.00	7.00	7.00	70.00
Management systems	6.33	6.00	6.17	61.67
Compliance	7.00	8.33	7.67	76.67
Culture	8.00	6.67	7.33	73.33
Leadership	6.00	6.33	6.17	61.67
Competence	6.00	6.00	6.00	60.00
MDfinal				62.12

Authors, based on collected data (2018).

6.5.2 Quality 4.0 maturity in the energy industry

The three quality leaders of the second studied company, who responded to the instrument developed in the present work, have also been working in the company for over 10 years. Table 6.4 indicates the average of the answers to the two questions

from each of the dimensions studied, as well as the average of each question per dimension and the organization maturity degree regarding Quality 4.0.

With reference to the data dimension (66.67%), unlike the automotive company, information of different natures is available in a common model and everyone in the organization has access to it. The company's information is updated periodically as in the first case study. However, this company is at the same level as the automotive industry regarding its frequency and its method about analytics (63.33%).

The connectivity in the energy industry, in turn, achieved an average dimension score of 6.67, indicating that the connectivity of people in the enterprise is controlled and only the highest hierarchical positions can enjoy smart devices. Also, frequent feedback is conducted by customer satisfaction online surveys and the data are automatically computed.

On the other hand, the collaboration aspect proved to be a bottleneck in implementing Industry 4.0 when considering the quality department in the studied company, since the organization had a low maturity degree in relation to this indicator (36.67%). Blockchain is not a company investment plan yet, while EQMS is already planned for the energy industry in order to provide real-time access to quality and manufacturing data for a synchronized view of the company.

It was observed that the energy company invests in app development through multiple interfaces which are segregated by functions and the interactions between them (mushups), but wearable devices have never been suggested as an investment for the organization, resulting in a weakness in advancing toward Quality 4.0 (46.67%).

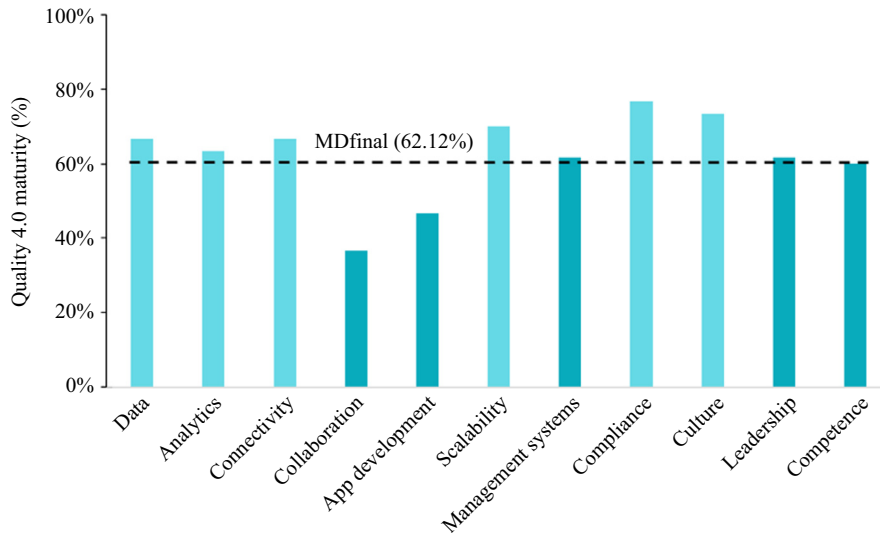
The concept of scalability presented the same characteristics found by the other company, however, punctuating a higher maturity degree regarding Quality 4.0 knowledge (70%).

Also, quality department practices in both companies refer to total quality management, where quality goes beyond the needs and expectations of customers and is a commitment by all levels of management. EQMS is already an enterprise investment plan to automate workflows, connect quality processes, improve data accuracy, and ensure compliance.

Regarding the compliance indicator, as in the scalability dimension, the energy company presented the same characteristics as the automotive company, but with a slightly higher degree of evolution in this dimension, since the energy industry suggests being closer to sharing success and failure approaches for compliance between groups and units in real time through Industry 4.0 mechanisms. This achieved the highest score among the Quality 4.0 dimensions (76.67%).

The second dimension that stood out refers to culture, with a development level of 73.33%, exposing the same characteristics as the automotive company relating to the quality culture knowledge by those who are not integrated in the department and, in addition, it provides the scale customization, business transparency, and error reduction.

It was observed that quality departments are following the transition to Industry 4.0 as it is deployed within the company and by their respective leaders. Leaders still plan to enhance quality by improving the application of basic and advanced quality tools.

**FIGURE 6.7**

Maturity degree for each dimension and final maturity degree (MDfinal) obtained in Quality 4.0 for the energy company.

Authors, based on collected data (2018).

Finally, the organization under study has a learning management system for its employees with no digital simulation, culminating in a maturity degree of 60% in the competence category.

Fig. 6.7 illustrates the maturity degree obtained for each Quality 4.0 dimension by the automotive company, as well as its final maturity degree in Quality 4.0, inferring about the potentialities and weaknesses presented by the organization. It is concluded that the energy industry did not reach a Quality 4.0 practice score, resulting in a maturity level of 62.12%, and being classified as advanced quality, which is still at its earliest stage.

The organization presented as its main weaknesses collaboration and apps development, which represented a low maturity degree. In all other dimensions, the energy industry achieved a median Quality 4.0 development, so that the indicator maturity varied between 76.7 and 60%.

6.5.3 Weaknesses and potentialities identified

From the data obtained, it is of interest to characterize the profiles of the studied companies according to each dimension in order to point out the weaknesses and potentialities.

The multinational automotive company presented, as weakness points, the dimensions connectivity and scalability, obtaining average scores of 50 and 58.33%, respectively.

In fact, in the automotive industry connectivity has proven to be the quality indicator which is less helpful in the migration in order to support Industry 4.0 implementation. The new way of connecting people, machines, and data is essential for quality improvement as it democratizes the access and the use of technologies 4.0 across the enterprise, leading to an evolution related to its culture, leadership, collaboration, and compliance obligations.

Scalability, according to the definition given in [Jacob \(2017\)](#), refers to the ability to store data volume and analysis on a global scale, and it can make Quality 4.0 more effective to harmonize processes, lessons learned, and other practices throughout the company. Cloud computing contributes significantly to scalability, since the storage capacity is associated with elasticity and ensures location independence and implementation agility ([Rajabion et al., 2019](#)).

The energy company, in turn, has suggested weaknesses regarding collaboration (36.67%) and app development (46.67%).

Within this last dimension mentioned, it was found that, although the company achieved a high score average (8.00), the question that refers to the use of wearables as a personal development monitoring system scored only 1.33 points, which reduced the indicator's overall score in this company to 4.67.

It is important to note and highlight the collaboration characteristics for the energy company. While the EQMS is a plan for the company, the blockchain technology remains unknown to leaders who have also pointed out that it is not an investment plan. According to [Janssen et al. \(2020\)](#), unlike public blockchains such as Bitcoin or Ethereum, where nodes are anonymous and all information is publicly available, the corporative ones are generally authorized systems where only known partners are part of the network. This approach is often required by companies in order to ensure their confidential information is not shared with unknown third parties, which enables reliable peer-to-peer transactions and transaction data distribution across a network so that all authorized players can see the same information which is secured by cryptographic methods ([Yermack, 2017](#)).

Considering app development, the question about the use of wearable devices as personal development monitoring systems scored only 1.33 points, which reduced the indicator's overall score in this company to 4.67. Wearable devices can be used on the shop-floor, reducing employee fatigue, stress, and improving work speed and quality; or in other activities, services, and fields over all industries, delivering information from the specialist to the repair and maintenance services ([Min et al., 2019](#); [Yassae et al., 2019](#)).

Regarding the dimension of collaboration, it is important to note its characteristics for the energy company. While the EQMS issue is a plan for the company, the score average for this question is 7.33, the blockchain technology remains unknown to contributors who have also pointed out that it is not an investment plan foreseen by the organization currently.

Regarding the strengths presented by the companies in advancing to Industry 4.0, the culture dimension ranked as the first in the automotive company and second in the energy company.

According to [Zheng et al. \(2010\)](#), culture is the determining factor for the organization's basic beliefs, values, and norms, and is positively related to knowledge sharing. Thus, the implementation of an organizational culture that underpins knowledge management turns out to be the major factor for companies to appropriate the value of their knowledge base ([Donate and Guadamillas, 2010](#)).

The result of this multiple case study suggests that the culture indicator, which is the basis of the organizational structure for knowledge management, is following the migration in order to support Industry 4.0 implementation.

In the automotive company, with the highest score for Quality 4.0 maturity along with culture, there is also the competence dimension. According to [Gunasekaran et al. \(2019\)](#), in recent years, people management has been challenged to establish greater reciprocity with corporate strategies. The innovations applied in this management, therefore, have become significant practices in order to develop the employee who, consequently, contributes greatly to the organizational structure growth, development, and positioning in the labor market.

According to respondents, the automotive industry is advanced in development skills, as it already has learning management linked to digital simulation innovation to improve results. It suggests that machine learning and artificial intelligence are already applied in some sectors to improve employee knowledge and, consequently, to deliver higher quality results.

The compliance dimension, in turn, was the most evolved regarding migration monitoring to support the implementation of Industry 4.0 in the energy industry. Meanwhile, in the view of employees, success and failure approaches regarding compliance have not been shared in real time yet, and the organization is already focusing on improving control of this dimension through the technologies 4.0 application.

According to [Dimyadi and Amor \(2017\)](#), compliance constitutes the basis for the ethical culture definition in the company, and to meet compliance results in risk mitigation, and reducing financial damage and an unethical conduct reputation.

Therefore the use of technologies provided by Industry 4.0 in the conformity dissemination frequency and control in the company allows reaching all levels of the organization, generating increased employee satisfaction and, consequently, their commitment to the culture and improved quality of the offered products and services.

6.6 Comments and future perspectives

The advance of the Fourth Industrial Revolution, with innovation strategies through the connections between people, objects, and processes, gives rise to the need to understand the application of concepts and fundamentals of quality in the digital era.

Quality 4.0 refers to the quality management digitization in Industry 4.0, and different perspectives should be considered in order to enable an assertive

implementation, and thus to monitor the productive environment progress toward the acquisition of new technologies.

A framework was developed to assess the degree of alignment between the quality department and Industry 4.0 in companies, proposing a five-stage maturity scale based on two parameters for each of the Quality 4.0 dimensions.

In order to allow assertive monitoring of Quality 4.0 maturity, considering the company's strategy, a systematic application of the framework to enable the use of historical data to predict scenarios, using a numerical approach, was suggested. This maturity monitoring, developed through the programmed application of the instrument for quality leaders, will allow the company to identify weaknesses and potentialities, and then execute route corrections and decision-making aligned with organizational goals.

The Quality 4.0 framework was used in a multiple case study, considering automotive and energy multinational industries. It was concluded that both companies are in an initial level of advanced quality, demonstrating quality alignment plans with Industry 4.0 attributes and technologies.

Organizational culture proved to be a strong point for Quality 4.0, with companies pointing out that culture has underpinned the implementation of Industry 4.0. Also, some improvement areas were identified, such as the need for investment in wearable devices and the use of blockchain in business.

As a continuation of this work, it is planned to apply the framework programmatically in these companies in order to create new diagnostics and help organizations to evaluate, in a practical way, their evolution in the Quality 4.0 pathway.

Therefore, the Quality 4.0 framework can be applied for scientific or practical purposes, and proved to be an assertive and easy tool to be used in companies in the process of implementation of Industry 4.0 practices and technologies. From the academy's point of view, this framework allows for the collection of data from different companies on the technologies and processes developed as approaches to align the quality department with Industry 4.0, and even serve as a basis for potential identification of good practices.

Regarding practical results, the framework enables companies to continuously monitor their quality maturity in order to evaluate their practices according to the respective organizational strategy, allowing diagnostics-based route adjustments.

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Intelligent manufacturing as a social institute: Internal and external regulation

7

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7.1 Introduction

One of the latest tendencies in the development of the modern global economy, which covered all its participants (though to different extents), is the Fourth Industrial Revolution. This tendency envisages active digital modernization of economies of countries around the world. Though this process takes place simultaneously in all spheres of the economy, acquiring the form of online commerce in trade, online payments in the financial sphere, remote education in the sphere

of education, etc., the largest digital transformations are observed in industry, where they acquire the form of intellectual production.

Due to the high priority of digital modernization of industry in the process of the Fourth Industrial Revolution, the new technological mode is called Industry 4.0. Specifics of Industry 4.0 consist of full-scale automatization, which does not simply oust a human (employee) from certain production processes, as was common for previous industrial revolutions, but fully excludes him from production, assigning the human (employee) with a completely new production function, which envisages organization and control over the work of machines.

Intellectual production is an innovative approach to the organization of production processes in industry in the conditions of Industry 4.0, according to which machines (digital technical devices) are under the control of artificial intelligence (AI), which is programmed by humans. Thus, depending on the specifics of a company's activities and the applied technologies, it is possible to plan production and program AI with further control of the quality of finished products. The process of production might not require control or be controlled by humans remotely.

Intelligent manufacturing is preceded by "smart" manufacturing, which also envisages integration of technical devices ("smart" machines that could exchange information) into a unified cyber-physical system, due to usage of the Internet of Things, but is controlled by a human (not by AI—as in the case of intelligent manufacturing). "Smart" factories have been created around the world (e.g., in the car industry). Manufacturing at these factories is organized on the basis of automatic conveyor lines, manipulators, and robots. However, they are controlled by humans—though with intelligent technologies of decision support. The essence of "smart" manufacturing is studied in the works by Mia et al. (2019), Zhang et al. (2019), and Hu et al. (2019).

Exclusion of humans from the process of intellectual production predetermines its predominantly anthropogenic nature. This means that intellectual production does not have social interactions—it contains only programmed algorithms of actions, in which the participants are inanimate technical devices. This is seen from the works by Ay et al. (2018), Teti et al. (2018), and Liang et al. (2018).

Contrary to this, we think that this has a very vivid and significant social nature, being a social institute—a system that is characterized by a public (social) structure and that envisages social interactions with human participation.

Institutionalization is the process of the formation of a social institute—that is, establishment of the existing (traditional) and successful social practices (practices of interaction of humans and implementation of their social roles). In the case of intellectual production in the conditions of Industry 4.0, social interactions take place not only between humans but also between machines (the Internet of Things) and between humans and machines (AI).

Based on this, we offer a working hypothesis that insufficient attention to social manifestations of intellectual production slows down its institutionalization: the implemented practices of the internal and external regulation of intellectual

production do not have significant positive effect that is connected to its increase (increase of its volume and share in the structure of industrial production).

That is why the purpose of the chapter is to study the process of institutionalization of intellectual production as an innovative approach to the organization of the production processes in industry in the conditions of Industry 4.0. The selected purpose predetermined the following tasks, which are solved in the course of the research. First, the effectiveness of the existing practices of internal and external stimulation of development of intellectual production is evaluated, and their drawbacks and limitations from the institutional point of view are determined. Then, innovative practices for quick and successful institutionalization of intellectual production are offered. After that, a conceptual model of intellectual production as a social institute is developed, and the algorithm of institutionalization of intellectual production, which reflects the essence and logic of this process, is offered. Also, the authors' recommendations for its practical implementation in technologically advanced countries around the world are offered.

7.2 Literature review

The foundations and applied issues of transition to Industry 4.0 in the process of digital modernization of the modern economy are studied in detail and described in multiple works. [Diez-Olivan et al. \(2019\)](#) note the necessity for quick and secure exchange of digital data and development of the system of machine learning for development of Industry 4.0 as an environment in which machines interact with each other without human participation. This is also noted in the work by [Romeo et al. \(2019\)](#). The systemic character of automatization, which covers the production and distributive processes in the conditions of Industry 4.0, and the necessity for the transfer of technologies in the added-value chains are emphasized in the work by [da Silva et al. \(2019\)](#).

The complexity of organization and the necessity for preparation for a transition to Industry 4.0 through preliminary pilot and separate digitization of the production processes in industry by the example of EU countries is shown in the work by [Castelo-Branco et al. \(2019\)](#). The scientific and methodological provision of measuring and evaluation of technical readiness of economic systems of various levels for transition to Industry 4.0 is provided by [Basl and Doucek \(2019\)](#), [Popkova \(2019\)](#), [Bogoviz \(2019\)](#), and [Popkova et al. \(2019\)](#). The perspective technical solutions for acceleration of transition to Industry 4.0 (e.g., "cloud robots") are offered by [Aissam et al. \(2019\)](#). [Popkova and Sergi \(2019\)](#) note the positive influence of Industry 4.0 on economic growth.

Priority and wide perspectives of the development and distribution of "smart" technologies in the conditions of Industry 4.0 are emphasized by [D'Emilia et al. \(2019\)](#). Foundations of Industry 4.0 on the digital platform and the importance of

provision of its reliability and safety are emphasized in Müller (2019). Specifics of planning and control of industrial production due to its machine organization are noted in Bendul and Blunck (2019). The computer (machine) environment of Industry 4.0 is studied by Verba et al. (2019).

Self-organization (autonomy) of industrial production due to full automatization of the production cycle in the conditions of Industry 4.0 is emphasized in Candanedo (2019) and Lopez et al. (2019). The essence and specific features of intellectual production are determined and outlined in a whole range of works by different scholars and experts. Each work considers certain technologies of Industry 4.0. For example, Liu et al. (2019) studied machine communications and information systems, Mia et al. (2019) studied “smart” technologies, Zhang et al. (2019) described 3D print, and Hu et al. (2019) i-robots.

The practical examples of organization of intellectual production in various spheres and different countries around the world are discussed in Ay et al. (2018) (intelligent robotic fish for bio-inspired swimming modes), Teti et al. (2018) (intelligent computation in design and manufacturing), and Liang et al. (2018) (multiple cases). The organizational and technical solutions to various problems of intellectual production are offered by Nielsen et al. (2018) (modeling of optimization algorithms of intellectual production), Day (2018) (perspectives of using robots in intellectual production), and Bingöl and Kılıçgedik (2018) (gene expression programming).

Thus, the performed literature review on the selected topic showed that despite the high level of elaboration of the technical aspects of implementation of intellectual production in the conditions of Industry 4.0, institutional (social) aspects are poorly studied and require further elaboration. This gap in the system of the existing knowledge is filled by this chapter. Its novelty and originality, as compared to existing works, consists in studying intellectual production in the conditions of Industry 4.0 as a social institute and development of recommendations for its regulation through institutionalization.

7.3 Materials and method

In order to verify the offered hypothesis, we use the method of regression analysis, which allows for full and precise determination of the presence and strength of the connection between various factors of internal and external regulations and the results of the development of intellectual production in the conditions of Industry 4.0. The resulting variables, which reflect the development of intellectual production in the conditions of Industry 4.0, are volume of hi-tech production, share of hi-tech production in the structure of export (statistics by the World Bank), and index of automatization (calculated by the Economist Intelligent Unit), calculated for separate countries. We supplement these with data for other countries with the help of expert evaluations.

The factors of internal regulation of the development of intellectual production in the conditions of Industry 4.0 are aggregate expenditures for R&D in the economy (as the indicator of financial provision of digital modernization, statistics by the World Bank) and marketing activity of entrepreneurship (indicator 11.08 “Extent of marketing” is calculated within the report “The Global Competitiveness Report” of the World Economic Forum).

The factors of external regulation of development of intellectual production in the conditions of Industry 4.0 are stimulation of R&D by the state, including protection of intellectual property (indicator “Regulatory framework”), telecommunication infrastructure (indicator “Technological framework”), and digital society (population that has digital competencies and set demand for the products of intellectual production) (indicator “Adaptive attitudes”), calculated by the IMD within the Digital Competitiveness Report, and tax load on business (Total tax rate, % of commercial profits) (statistics by the World Bank).

In order to obtain the most objective and accurate results, we included 15 developed (positions 1–15 in the global rating of digital competitiveness) and developing (positions 27–42 in the global rating of digital competitiveness, except for Italy) countries in the selection. The research is performed based on the data for late 2018–early 2019. The initial statistical data for the research are given in [Tables 7.1 and 7.2](#).

[Table 7.1](#) shows that on average in the selection of developed and developing countries, which have the highest level of digital competitiveness and, therefore, the highest potential and highest progress in development of intellectual production in the conditions of Industry 4.0, the volume of hi-tech production constitutes 0.42% of added value in industry. The coefficient of variation (data scatter) equals 27.1%.

Average volume of hi-tech export in 2018 in the selection of countries constituted USD 44,870,551,340; coefficient of variation constituted 116.4%. The average index of automatization constituted 27.98 points; coefficient of variation—101.6%. Average expenditures for R&D equaled 1.75% of GDP, coefficient of variation—54.7%. Marketing activity of entrepreneurship constituted 4.93 points, coefficient of variation—8.7%. On the whole, according to the results of the analysis of variation, the initial selection is heterogeneous (large scatter), which could distort the results of the regression analysis.

As is seen from [Table 7.2](#), on average in the selection of developed and developing countries, which have the highest level of digital competitiveness and therefore the highest potential and which achieved the highest progress in the development of intellectual production in the conditions of Industry 4.0, stimulation of R&D is ranked 23rd in the world, and the coefficient of variation equals 51.15%.

Telecommunication infrastructure is ranked 23rd in the world on average, and the coefficient of variation equals 52.15%. Digital society is ranked 23rd in the world on average, and the coefficient of variation equals 60.68%. Tax load of business is assessed at 35.52% of commercial profit on average, and the coefficient of

Table 7.1 Factors of internal regulation and results of development of intellectual production in the conditions of Industry 4.0 in 2018 (the higher the better).

Position in the global rating of digital competitiveness		Country	Volume of hi-tech production, % of added value in industry	Volume of hi-tech export, USD thousands	Index of automization, points 0–100	Expenditures for R&D, % of GDP	Marketing activity of entrepreneurship, points 0–7
			y_1	y_2	y_3	x_1	x_2
Developed countries	1	United States	0.47	110120235.61	72.8	2.74	6.0
	2	Singapore	0.81	136160944.49	87.5	2.18	5.2
	3	Sweden	0.54	14973092.21	12.5 ^a	3.25	5.5
	4	Denmark	0.53	7467358.20	17.5 ^a	2.87	5.0
	5	Switzerland	0.64	24159696.00	5.8 ^a	3.37	3.7
	6	Norway	0.50	3590613.20	29.2 ^a	2.03	5.2
	7	Finland	0.40	3571518.72	14.6 ^a	2.75	4.2
	8	Canada	0.31	24220179.63	82.6	1.61	5.0
	9	Netherlands	0.48	63617214.21	6.3 ^a	2.03	5.6
	10	United Kingdom	0.48	68625231.69	75.6	1.69	5.8
	11	Hong Kong (SAR)	0.34	141717301.21	8.0 ^a	0.79	5.3
	12	Israel	0.43	7358944.00	4.4 ^a	4.25	5.5
	13	Australia	0.30	4322994.33	71.5	1.92	5.2
	14	South Korea	0.63	72699710.20	91.3	4.24	4.8
	15	Austria	0.45	12943326.47	4.2 ^a	3.09	5.2

Developing countries	27	Malaysia	0.42	41172608.99	58.2	1.30	5.5
	28	Qatar	0.62	4815.20	2.9 ^a	0.51	5.1
	29	Lithuania	0.20	2160520.24	4.0 ^a	0.85	4.7
	30	China	0.41	504380837.92	68.5	2.11	4.6
	31	Spain	0.39	15566761.96	3.0 ^a	1.19	4.6
	32	Portugal	0.26	2350793.41	2.2 ^a	1.27	4.6
	33	Czech Republic	0.50	21069666.19	4.9 ^a	1.68	4.7
	34	Slovenia	0.49	1518763.43	1.9 ^a	2.00	4.3
	35	Latvia	0.21	1333535.71	3.4 ^a	0.44	4.5
	36	Poland	0.37	13678247.82	2.4 ^a	0.97	4.7
	37	Chile	0.15	589579.68	2.1 ^a	0.37	5.1
	38	Kazakhstan	0.16	1771744.27	2.1 ^a	0.14	4.1
	39	Thailand	0.41	34720646.34	3.1 ^a	0.62	5.1
	40	Russia	0.26	9174217.41	52.2	0.10	4.5
	42	Saudi Arabia	0.41	1075441.33	44.8	0.09	4.6
Direct average			0.42	44870551.34	27.98	1.75	4.93
Standard deviation			0.11	52215174.4	28.43	0.96	0.43
Coefficient of variation, %			27.1	116.4	101.6	54.7	8.7

Compiled by the authors based on *The Economist Intelligent Unit, 2019. The automation readiness index: who is ready for the coming wave of automation?* Available from: <<http://www.automationreadiness.eiu.com>> (accessed 19.04.19.), *IMD, 2019. World Digital Competitiveness Ranking 2018*. Available from: <<https://www.imd.org/wcc/world-competitiveness-center-rankings/world-digital-competitiveness-rankings-2018/>> (accessed 19.04.19.), *World Bank, 2019a. Medium- and High-Tech Manufacturing Value Added share in total manufacturing value added*. Available from: <https://tcddata360.worldbank.org/indicators/hbe238413?country=BFA&indicator=3794&viz=line_chart&years=1990,2014> (accessed 19.04.19.), and *World Economic Forum, 2019. The Global Competitiveness Report 2017–2018*. Available from: <<http://www3.weforum.org/docs/GCR2017-2018/05FullReport/TheGlobalCompetitivenessReport2017-2018.pdf>> (accessed 19.04.19.).

^aData are determined by the authors with the method of expert evaluation.

Table 7.2 Factors of internal regulation and results of development of intellectual production in the conditions of Industry 4.0 in 2018 (the higher the better).

Position in the global rating of digital competitiveness		Country	Stimulation of R&D, position in the world 1–63 x_3	Tax load on business, % of commercial profit x_4	Telecommunication infrastructure, position in the world 1–63 x_5	Digital society, position in the world 1–63 x_6
Developed countries	1	United States	16	43.8	9	1
	2	Singapore	2	20.6	1	20
	3	Sweden	12	49.1	7	9
	4	Denmark	8	23.8	5	5
	5	Switzerland	15	28.8	15	12
	6	Norway	1	37.0	3	8
	7	Finland	4	37.3	6	6
	8	Canada	11	20.5	24	15
	9	Netherlands	10	40.8	14	7
	10	United Kingdom	7	30.0	17	4
	11	Hong Kong (SAR)	14	22.9	11	11
	12	Israel	30	26.2	20	17
	13	Australia	6	47.4	19	2
	14	South Korea	27	33.1	2	3
	15	Austria	24	51.5	21	25

Developing countries	27	Malaysia	29	39.2	32	30
	28	Qatar	32	11.3	30	16
	29	Lithuania	28	42.6	22	41
	30	China	26	64.9	40	23
	31	Spain	36	47.0	29	26
	32	Portugal	19	39.8	39	35
	33	Czech Republic	44	46.1	18	34
	34	Slovenia	42	31.0	45	44
	35	Latvia	31	36.0	26	52
	36	Poland	46	40.7	37	33
	37	Chile	33	34.0	41	27
	38	Kazakhstan	22	29.4	42	47
	39	Thailand	34	29.5	28	55
	40	Russia	38	46.3	38	39
	42	Saudi Arabia	50	15.7	56	43
Direct average			23.23	35.52	23.23	23.00
Standard error			11.88	9.39	12.12	16.30
Coefficient of variation, %			51.15	26.41	52.15	60.68

Compiled by the authors based on [IMD, 2019](https://www.imd.org/wcc/world-competitiveness-center-rankings/world-digital-competitiveness-rankings-2018/). World Digital Competitiveness Ranking 2018. Available from: <<https://www.imd.org/wcc/world-competitiveness-center-rankings/world-digital-competitiveness-rankings-2018/>> (accessed 19.04.19.) and [World Bank, 2019b](https://data.worldbank.org/indicator/IC.TAX.TOTL.CP.ZS). World Development Indicators: Total tax rate (% of commercial profits). Available from: <<https://data.worldbank.org/indicator/IC.TAX.TOTL.CP.ZS>> (accessed 19.04.19.).

variation equals 26.41%. On the whole, the selection of the data is heterogeneous (large scatter), which could distort the results of regression analysis.

7.4 Results

7.4.1 Evaluation of the effectiveness of the existing practices of internal and external stimulation of the development of intellectual production from the institutional point of view

The coefficients of autocorrelation are now calculated (based on the data in [Tables 7.1 and 7.2](#)) for preliminary evaluation of the potential influence of the implemented practices of internal and external stimulation on the development of intellectual production in the selection of developed and developing countries, which have the highest level of digital competitiveness and therefore the highest potential and which achieved the highest progress in development of intellectual production in the conditions of Industry 4.0. The results of these calculations are shown in [Table 7.3](#).

According to the data in [Table 7.3](#), the highest autocorrelation y_1 is observed with x_1 (0.579961), x_5 (−0.536574), and x_6 (−0.464798). Autocorrelation y_2 and y_3 with all potential factors is low (does not reach 0.5). That is why we compile the models of multiple linear regression of the form $y_1 = \delta + \lambda_1 \times x_1 + \lambda_2 \times x_2 + \dots + \lambda_n \times x_n$, where δ is the design constant, $\lambda_1, \lambda_2, \dots, \lambda_n$ are the design coefficients with variable x , which show the change of y with an increase of corresponding x by 1. The characteristics of regression model $y_1(x_1, x_5, x_6)$ are shown in [Table 7.4](#).

P -values in [Table 7.4](#) show that the only statistically significant factor of regulation at the significance level $\alpha = 0.05$, which has potential influence on the development of intellectual production, is x_1 —as only its design coefficient does not exceed 0.05 (P -value $\lambda_1 = .0776$). P -values of other estimate coefficients (P -value $\lambda_5 = .2652$, P -value $\lambda_6 = .9327$) exceed 0.05 and therefore the corresponding variables do not have statistically significant (at the level $\alpha = 0.05$) influence on the resulting variable and thus should be excluded from the regression model. We perform separate regression analysis of dependence $y_1(x_1)$. The characteristics of the obtained model of paired linear regression are shown in [Table 7.5](#).

Table 7.3 Coefficients of autocorrelation of the implemented practices of internal and external stimulation and development of intellectual production.

	x_1	x_2	x_3	x_4	x_5	x_6
y_1	0.579961	0.191789	−0.253298	−0.240680	−0.536574	−0.464798
y_2	0.126468	0.089239	−0.115271	0.367321	−0.005320	−0.158856
y_3	0.206331	0.318363	−0.320651	0.011624	−0.227820	−0.403666

Table 7.4 Characteristics of the regression model $y_1(x_1, x_5, x_6)$.

Regression statistics						
Multiple R			0.6178			
R^2			0.3817			
Adjusted R^2			0.3103			
Standard error			0.1253			
Observations			30			
Dispersion analysis						
	df	SS	MS	F	Significance F	
Regression	3	0.2521	0.0841	5.3499	0.0053	
Residue	26	0.4085	0.0157			
Total	29	0.6607				
	Coefficients	Standard error	t-Stat	P-value	Lower 95%	Upper 95%
Δ	0.3995	0.0954	4.1883	.0003	0.2035	0.5956
λ_1	0.0503	0.0274	1.8376	.0776	− 0.0060	0.1066
λ_5	− 0.0028	0.0024	− 1.1388	.2652	− 0.0078	0.0022
λ_6	− 0.0002	0.0022	− 0.0853	.9327	− 0.0046	0.0043

Calculated and compiled by the authors in Microsoft Excel with the help of the function "Data analysis: regression."

Table 7.5 Characteristics of the regression model $y_1(x_1)$.

Regression statistics						
Multiple R			0.5800			
R^2			0.3364			
Adjusted R^2			0.3127			
Standard error			0.1251			
Observations			30			
Dispersion analysis						
	Df	SS	MS	F	Significance F	
Regression	1	0.2222	0.2222	14.1912	0.0008	
Residue	28	0.4385	0.0157			
Total	29	0.6607				
	Coefficients	Standard error	t-Stat	P-value	Lower 95%	Upper 95%
δ	0.2896	0.0413	7.0171	1.24E-07	0.2050	0.3741
λ_1	0.0740	0.0197	3.7671	.0008	0.0338	0.1143

Calculated and compiled by the authors in Microsoft Excel with the help of the function "Data analysis: regression."

The performed calculations allow compiling of the following model of paired linear regression: $y_1 = 0.2896 + 0.0740 \times x_1$. According to the obtained model, growth of expenditures for R&D by 1% of GDP lead to an increase of the volume of hi-tech production by 0.0740% of added value in industry. The obtained P -values of constant (1.24E-07) and variable (0.0008) do not exceed 0.05—therefore the compiled regression model is correct and authentic at the significance level $\alpha = 0.05$. At the same time, the obtained value $R^2 = 0.3364$ shows a weak connection between the dependent and independent variables: the change of the volume of hi-tech production by 33.64% is explained by the change of expenditures for R&D.

The observed value of F -test (14.1912) does not exceed the table value, which, with $\alpha = 0.05$, $k_1 = m = 1$, and $k_2 = n - m - 1 = 30 - 1 - 1 = 28$, constitutes 2.89, which shows statistical significance of the obtained regression equation. This is confirmed by verification with the help of Student's t -test, which has an observed value (3.7671) that does not exceed the table value, which, with $P = .05$ and $n - 2 = 30 - 2 = 28$, constitutes 2.049. This allows for stating that the dependence of the volume of hi-tech production on expenditures for R&D is strong, direct, and sustainable.

Characteristics of the regression model $y_2(x_1, x_2, x_3, x_4, x_5, x_6)$ are shown in Table 7.6.

R -values of all design coefficients in Table 7.6 (P -value $\lambda_1 = .8029$, P -value $\lambda_2 = .8258$, P -value $\lambda_3 = .5562$, P -value $\lambda_4 = .0743$, P -value $\lambda_5 = .3418$, P -value $\lambda_6 = .5708$) exceed 0.05 and therefore the corresponding variables do not have a statistically significant (at the level $\alpha = 0.05$) influence on the resulting variable, and, thus, the regression model is incorrect. Further deep regression analysis of this model with the help of regression statistics, dispersion analysis, and application of F -test and Student's t -test is not expedient.

The characteristics of the regression model $y_3(x_1, x_2, x_3, x_4, x_5, x_6)$ are shown in Table 7.7.

R -values of all design coefficients in Table 7.6 (P -value $\lambda_1 = .9277$, P -value $\lambda_2 = .3939$, P -value $\lambda_3 = .5600$, P -value $\lambda_4 = .9529$, P -value $\lambda_5 = .4929$, P -value $\lambda_6 = .3241$) exceed 0.05 and therefore the corresponding variables do not have a statistically significant (at the level $\alpha = 0.05$) influence on the resulting variable, and, thus, the regression model is not correct. Further deep regression analysis of this model with the help of regression statistics, dispersion analysis, and application of F -test and Student's t -test is not expedient.

Thus, the results of the performed evaluation showed low effectiveness of the existing practices of internal and external stimulation of the development of intellectual production. From an institutional point of view, this could be explained by insufficient attention to social manifestations of intellectual production and the necessity for their consideration for improving these practices and developing the innovative practices of stimulation of development of intellectual production for its quick and successful institutionalization.

Table 7.6 Characteristics of the regression model $y_2(x_1, x_2, x_3, x_4, x_5, x_6)$.

Regression statistics						
Multiple R				0.4425		
R^2				0.1958		
Adjusted R^2				− 0.0140		
Standard error				96147775.9780		
Observations				30		
Dispersion analysis						
	Df	SS	MS	F	Significance F	
Regression	6	5.17633E + 16	8.62721E + 15	0.9332	0.4902	
Residue	23	2.12621E + 17	9.24439E + 15			
Total	29	2.64384E + 17				
	Coefficients	Standard error	t-Stat	P-value	Lower 95%	Upper 95%
Y-intercept	− 106349409.3566	235664792.1626	− 0.4513	.6560	− 593859172.3888	381160353.6756
x1	5785193.9374	22917792.2455	0.2524	.8029	− 41623871.1346	53194259.0093
x2	8785168.3849	39474606.5209	0.2226	.8258	− 72874276.3467	90444613.1165
x3	− 1249296.0553	2091943.7404	− 0.5972	.5562	− 5576811.3698	3078219.2592
x4	2919122.4515	1560939.3705	1.8701	.0743	− 309926.6383	6148171.5413
x5	2129713.9634	2194143.2624	0.9706	.3418	− 2409217.1687	6668645.0956
x6	− 1148510.9527	1997191.5928	− 0.5751	.5708	− 5280016.5170	2982994.6116

Calculated and compiled by the authors in Microsoft Excel with the help of the function "Data analysis: regression."

Table 7.7 The characteristics of the regression model $y_3(x_1, x_2, x_3, x_4, x_5, x_6)$.

Regression statistics						
Multiple R			0.4553			
R^2			0.2073			
Adjusted R^2			0.0005			
Standard error			32.1904			
Observations			30			
Dispersion analysis						
	Df	SS	MS	F	Significance F	
Regression	6	6232.7313	1038.7886	1.0025	0.4475	
Residue	23	23833.0303	1036.2187			
Total	29	30065.7617				
	Coefficients	Standard error	t-Stat	P-value	Lower 95%	Upper 95%
Y-intercept	− 17.7384	78.9008	− 0.2248	.8241	− 180.9571	145.4802
x1	0.7034	7.6729	0.0917	.9277	− 15.1692	16.5760
x2	11.4829	13.2161	0.8689	.3939	− 15.8567	38.8226
x3	− 0.4142	0.7004	− 0.5914	.5600	− 1.8631	1.0346
x4	0.0312	0.5226	0.0597	.9529	− 1.0499	1.1123
x5	0.5119	0.7346	0.6969	.4929	− 1.0077	2.0315
x6	− 0.6737	0.6687	− 1.0076	.3241	− 2.0570	0.7095

Calculated and compiled by the authors in Microsoft Excel with the help of the function "Data analysis: regression."

7.4.2 Innovative practices of stimulation of the development of intellectual production for its quick and successful institutionalization

From an institutional point of view, financing of R&D in the sphere of intellectual production is an important practice, which is successfully implemented in the selection of developed and developing countries that have the highest level of digital competitiveness and therefore the highest potential, and that achieved the largest progress in the development of intellectual production in the conditions of Industry 4.0. However, for quick and successful institutionalization it has to be supplemented by other practices. For this, it is suggested to improve the existing practices of stimulation of development of intellectual production (Table 7.8).

As can be seen from Table 7.8, the process of marketing of intellectual production includes the promotion of products that are created with the help of intellectual production—that is, post-production marketing (sales marketing) is conducted, which is aimed at the artificial creation of needs. Thus, the demand

Table 7.8 Improving the existing practices of stimulation of the development of intellectual production for its quick and successful institutionalization.

	Practice	Existing approach for implementation of the practice	Offered approach for implementation of the practice
Internal	Marketing of intellectual production	Promotion of products that are created with the help of intellectual production (artificial creation of needs)	Conducting marketing research for determining the objective (natural) needs for products that are manufactured with the help of intellectual production
External (state)	Non-tax stimulation of R&D in the sphere of intellectual production	Separate protection of intellectual property in different countries	Global system of protection of intellectual property in different countries
	Tax stimulation of R&D in the sphere of intellectual production	Common tax regime for business	Special tax regime for business that conducts intellectual production in the conditions of Industry 4.0
	Development of the telecommunication infrastructure for intellectual production	Development of standard digital technologies (computer equipment, Internet, mobile communications, etc.)	Development of breakthrough digital technologies (AI, Internet of Things, blockchain, etc.)
	Development of digital society for stimulation of demand for intellectual production	Development of only digital competencies	Additionally: increase of susceptibility to changes

Developed and compiled by the authors.

for products that are created with the help of intellectual production (as a rule, hi-tech and innovative products) is formed under the influence of fashion.

As an alternative, we offer preliminary marketing, which is aimed at conducting marketing research for determining the objective (natural) needs for the products that are manufactured with the help of intellectual production. This will allow balancing demand and offering hi-tech and innovative products in the conditions of Industry 4.0 and supporting demand by the necessity for its practical application (value of its functional qualities).

The performed non-tax stimulation of R&D in the sphere of intellectual production envisages separate protection of intellectual property in different

countries. This complicates the process of transnationalization of hi-tech business and causes “copying of innovations,” instead of the creation of completely new innovations. From an institutional point of view, the global system of protection of intellectual property in different countries, which is regulated by international organizations, is preferable.

Tax stimulation of R&D in the sphere of intellectual production envisages a common tax regime for business—that is, absence of tax preferences. We suggest to create a special tax regime for business that conducts intellectual production in the conditions of Industry 4.0, which would provide tax preferences (tax subsidies, vacations, and credits), thus stimulating its development. Development of the telecommunication infrastructure for intellectual production is conducted with the help of development of standard digital technologies (computer equipment, the Internet, mobile communications, etc.). In our opinion, development of breakthrough digital technologies (AI, the Internet of Things, blockchain, etc.) is preferable.

The development of a digital society for the stimulation of demand for intellectual production envisages the development of only digital competencies (e.g., skills with computer equipment and the Internet). We offer to increase society’s susceptibility to changes and to stimulate the inclination for innovations for increasing the demand for hi-tech and innovative products that are created with the help of intellectual production.

Second, we offer the following innovative (not implemented now or implemented fragmentarily; not considered in the official statistics) practices of stimulation of development of intellectual production for its quick and successful institutionalization:

- Integration in the sphere of hi-tech: usage of external and internal integration mechanisms (e.g., clusters, technological parks, and innovative networks) will allow the forming and strengthening of connections between business structures that conduct intellectual production between themselves and with suppliers of resources (financial, intellectual, material, etc.), thus developing the transfer of hi-tech, joint marketing, and intellectual production (reducing costs and increasing efficiency);
- Development of public–private partnerships: this practice should be aimed at starting intellectual production in the markets and market segments where “market gaps” are observed due to a deficit of financial resources (low attractiveness for private investors) or low competition (insufficient concentration of market or market segment);
- Business education: the development of entrepreneurial capabilities with owners and managers of businesses, which would allow them to start and develop intellectual production, and the transfer of perspective ideas for business, as well as teaching practical foundations of the application of technologies of intellectual production.

7.4.3 Modeling of the institutionalization of intellectual production and practical recommendations (policy implications)

A vivid social component of intellectual production predetermines the incorrectness of its traditional image as a closed technical system with predominantly machine communications. Contrary to this, we deem it necessary to present intellectual production as a social institute—that is, a system with developed and important social connections and relations—both internal and external. The offered conceptual model of intellectual production as a social institute is shown in Fig. 7.1.

According to Fig. 7.1, intellectual production is not a separate closed business structure that developed automatization of its production processes (according to the traditional image) but a totality of integrated business structures (A,B,C,...N), which conduct joint intellectual production at all stages of the added-value chain. These structures also conduct transfer of technologies, competing with each other and supporting each other, thus stimulating the implementation of innovations and growth of efficiency.

Integrated business structures in the sphere of hi-tech use the scientific and educational platform, which provides them with digital personnel (according to the traditional image) and business education (developing the specific entrepreneurial skills, which are necessary for starting and conducting intellectual production). Scientific and educational establishments are a part of integrated structures (clusters, technological parks, and innovative networks). They also use developed

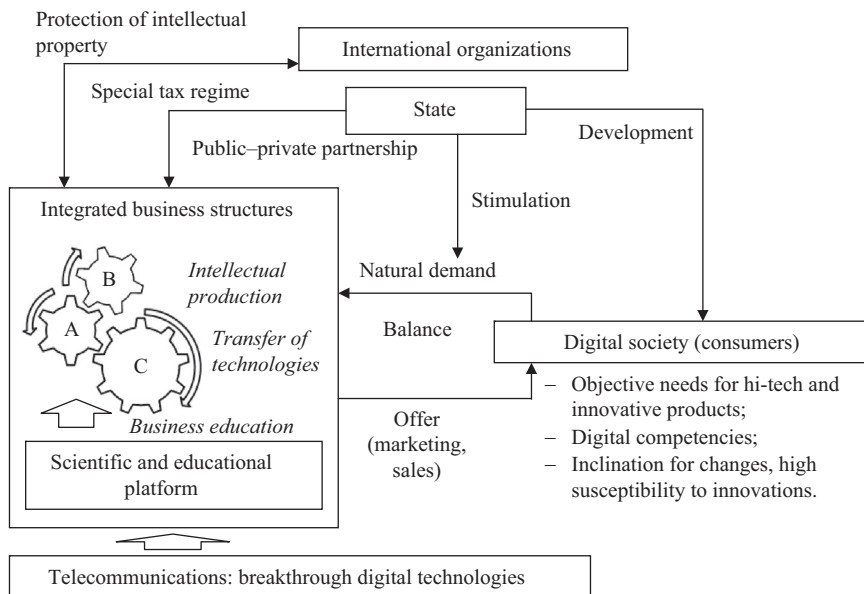


FIGURE 7.1 Conceptual model of intellectual production as a social institute.

Developed and compiled by the authors.

telecommunications: breakthrough digital technologies (e.g., AI, the Internet of Things, and blockchain).

In the external environment of integrated business structures, which conduct intellectual production, a digital society functions—it has objective needs for hi-tech and innovative products, possesses digital competencies, and is inclined toward changes, being susceptible to innovations. Consumers set natural demand for products that are created with intellectual production; integrated business structures conduct marketing and satisfy significant demand, selling their products. As a result, the balance of demand and offer is achieved.

The state stimulates the development of digital society (e.g., with the help of the development of the system of science and education) with natural demand for products that are created with intellectual production (e.g., through an increase of ecological norms and standards of energy efficiency), and creates and supports a special tax regime and partnership relations with integration business structures. International organizations conduct registration and protection of the intellectual properties of integrated business structures that conduct intellectual production.

Considering intellectual production as a social institute, it is possible to see that the process of its creation and sustainable functioning is more complex than traditionally offered simple purchase of new technologies and equipment. Institutionalization of intellectual production requires the observation of a certain sequence of stages, as shown in the developed algorithm (Fig. 7.2).

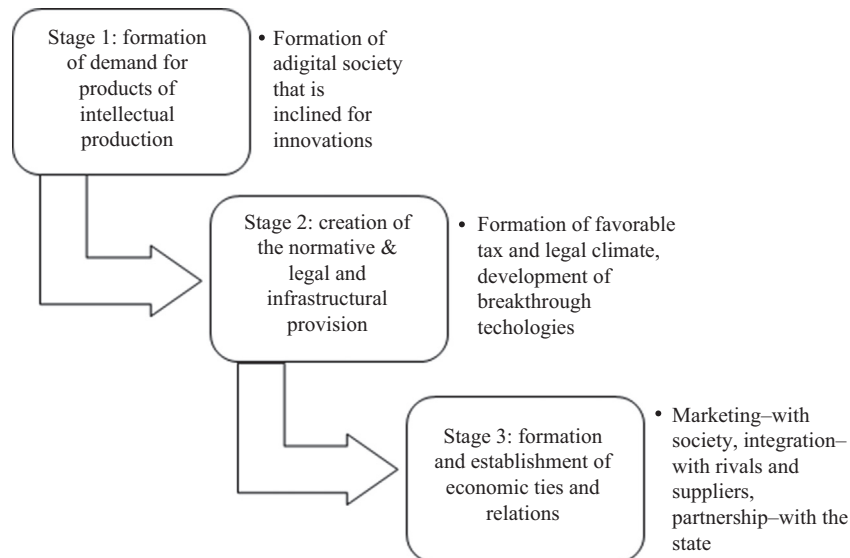
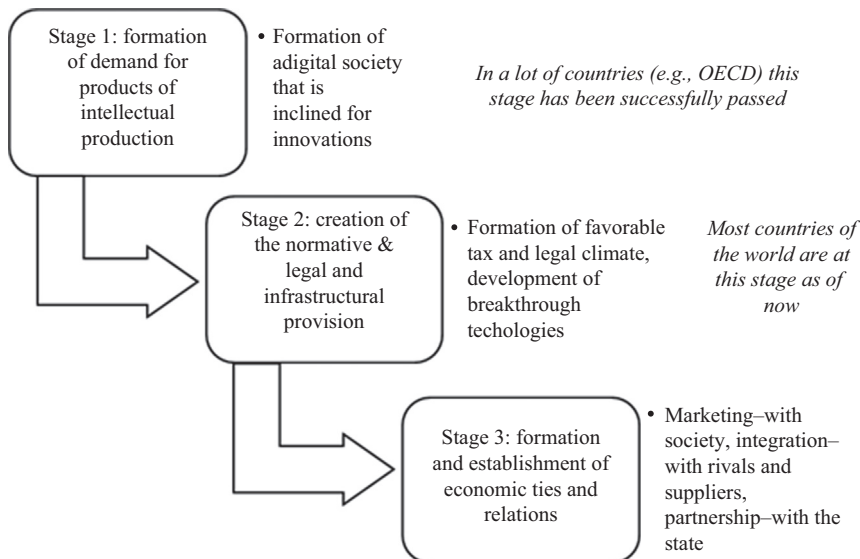


FIGURE 7.2 The algorithm of institutionalization of intellectual production.

Developed and compiled by the authors.

The algorithm in Fig. 7.2 reflects the essence and logic of the process of institutionalization of intellectual production. At the first stage, demand for products of intellectual production (hi-tech and innovative) is formed. This envisages the formation of a digital society, which is inclined toward innovations. There are natural preconditions for this in many countries, and this stage is already in the past. Countries within the OECD are examples of this.

At the second stage, the normative and legal and infrastructural provision of intellectual production is created. This envisages the formation of a favorable tax and legal climate and the development of breakthrough digital technologies. Most countries around the world are at this stage and implement national programs of digital modernization of economy and transition to Industry 4.0.



That is why, from the scientific point of view, the third stage is the most interesting one—it envisages the establishment of economic connections and relations within an open system of intellectual production. Marketing connections and relations are established with the society (consumers), integration connections—with rivals and suppliers, and partnership relations—with the state. For the formation of these relations and successful termination of the process of institutionalization of intellectual production in the more advanced countries around the world we offer the following recommendations in the sphere of internal regulation (for business structures):

- Increase of the marketing budget for intellectual production, together with financing of R&D for successful further commercialization of their results;
- Protection from strategies of market isolation and the search for means of integration with rivals and suppliers, as well as partnership with the state.

We also offer the following recommendations in the sphere of external regulation (for the state):

- Initiation of public—private partnership projects in the hi-tech sphere, which envisages starting intellectual production;
- Establishment of the cluster model of development of the regional economy, which envisages active formation and stimulation of development of regional clusters in the hi-tech sphere;
- Development of close international cooperation on the issues of simplification of the process of registration and guarantee of protection of intellectual property at the global level of the economy;

Practical implementation of the offered recommendations will allow eliminating the existing barriers on the path to finishing the process of institutionalization of intellectual production in the more advanced countries around the world. At the same time, there could be a need for additional specific practices of regulation of intellectual production, which could differ in various countries. For example, developing countries might need an increase of the level of real disposable incomes of population for raising the volume of effective demand for hi-tech and innovative products even with a formed digital society and its inclination toward innovations.

7.5 Conclusions

Thus, the obtained results confirm the offered hypothesis and show that intellectual production is more than a simple totality of digital technical devices that conduct automatized production of industrial products—as is provided in most of the existing works and publications on the topic of intellectual production, which offer separate technical solutions.

Intellectual production is a social institute and complex system, characterized by many social connections and relations. This is not to implement the opportunities of technological progress (as envisaged by the modern scientific paradigm) but to satisfy the society's needs. This requires full-scale usage of the integration mechanisms by hi-tech business through clusters, unification into technological parks and innovative networks, and participation in public—private partnership projects.

Thus, the applied practices of internal regulation of intellectual production, aimed at specialized financing of R&D and marketing support for sales of hi-tech and innovative products that are not in high demand in society, and the practice of external regulation (stimulation), connected to incomplete (only on a certain territory) protection of intellectual property, formation of a common tax climate for business, development of obsolete telecommunication infrastructure, and digital society, which has digital competencies but is not inclined toward their practical application and opposing innovations, show low effectiveness.

Intellectual production in the selection of developed and developing countries that have the highest level of digital competitiveness and therefore the greatest potential and that achieved the most progress in the development of intellectual production in the conditions of Industry 4.0, is at the starting point of its development. The average volume of hi-tech production in this selection of countries in 2018 constituted 0.42% of added value in industry, the volume of hi-tech export was — USD 44,870,551.34 (3% of GDP), and the average index of automatization was 27.98 points.

To solve the problem of acceleration of development of intellectual production in the more advanced countries in the world, we offer recommendations for improving the existing practices and outline the innovative practices of stimulation of development of intellectual production—integration in the sphere of hi-tech, development of public—private partnerships, and business education; and develop its conceptual model as a social institute and offer an algorithm for its institutionalization. It is determined that most of the more advanced countries in the world are at the second stage of this algorithm; the practical recommendations in the sphere of internal and external regulation of intellectual production are offered, which would allow finishing the process of its institutionalization.

It should be noted that defining intellectual production as a social institute does not only open new opportunities and perspectives for its regulation (stimulation) on the basis of development of social connections and relations but also shows the susceptibility of intellectual production to social risks. Further research should be devoted to determination of these risks and development of relevant scientific and methodological provisions.

Acknowledgments

This research was performed with financial support from the Russian Fund for Fundamental Research within scientific project No. 18-010-00103 A.

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Production planning and supply chain management under the conditions of Industry 4.0

8

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8.1 Introduction

The real sector (primarily industry) plays a very important role and might even be the basis of the national economy of most modern countries of the world. Despite the global post-industrialization of the late 20th–early 21st centuries, developed

and developing countries in the modern global economy specialize in various spheres of industry, as they have absolute or relative competitive advantages in these. Also, after the global financial recession (2008), the development of industry has been considered a means of macroeconomic stabilization.

Production planning and supply chain management are a central element of the entrepreneurial activities in industry for the following reasons. First, production planning and supply chain management determine the innovative development of entrepreneurship in industry. Technological innovations dominate in industry, so production and logistical processes are subject to changes, determining the flexibility of companies in industry. Another aspect of innovative activities in the sphere of production planning and supply chain management is that these entrepreneurial processes are very susceptible to risk and are thus the key directions of risk management.

Second, production planning and supply chain management determine the possibilities of selling industrial products. The more precise the list of initial needs of the representatives of the market target segment for the company's products and the fuller the products' satisfaction of these needs, the higher the probability of their sales, return of investments, and the company's profitability. At the macroeconomic level, this determines the level and quality of the population's life. The successfulness of production planning and supply chain management determines the possibilities for export of industrial products, opening the opportunities for expansion and diversification of the sales markets for companies in industry and helping to sustain a positive foreign trade balance and ensuring national economic security.

Third, production planning and supply chain management determine the effectiveness of entrepreneurship in industry. Production and sales processes are susceptible to optimization in the activities of companies in industry. Effectiveness is an important factor in the formation of the costs of industrial products. In the conditions of global competition, effectiveness is an important factor for the provision of competitiveness of companies in industry. These reasons predetermine the existence of various conceptual models of production planning and supply chain management, each of which takes into account the specific features of the context (sectorial or territorial, e.g., the business environment) and the activities of the companies that implement them (capabilities and strategic priorities).

Under the conditions of Industry 4.0, the key changes could and will take place in the sphere of production planning and supply chain management companies in industry. Automatization, which ensures the growth of labor efficiency and allows for the creation of new and development of existing hi-tech productions, requires planning and management for obtaining the expected (target) social (e.g., improvement of labor conditions) and economic (e.g., growth of production volume and reduction of production resource intensity) advantages.

In this chapter we offer hypothesis H_0 —the existing models, despite their advantages in a certain context for the corresponding companies, cannot be used under the conditions of Industry 4.0, as they do not allow for full-scale

optimization (on the basis of automatization) of the processes of production planning and supply chain management of companies in industry. This research aims to verify the offered hypothesis and seeks the goal of substantiating the necessity for and developing a new framework model of production planning and supply chain management under the conditions of Industry 4.0, as well as offering recommendations for adapting this model to the various regions of the world.

The set goal predetermined the logic and structure of the organization of this research, which is performed in three consecutive stages. In the first stage, regional models of production planning and supply chain management, which are formed in the modern global economy, are determined. In the second stage, a perspective model of production planning and supply chain management under the conditions of Industry 4.0 is developed. In the third stage, the perspective model of production planning and supply chain management under the conditions of Industry 4.0 is adapted to the various regions of the world.

8.2 Literature review

As a result of the selection and systematization of the existing literature on the topic of this research, we determined three areas of directions of creation, accumulation, and development of economic knowledge. First direction: the development of sectorial models of production planning and supply chain management. Within this direction, multiple case (empirical) studies with the example of various spheres of economy are conducted—this direction is studied in detail in the existing literature.

[Susarla and Karimi \(2018\)](#) point out the necessity for integration (systemic implementation) of the processes of production planning and management of reserves in a multinational pharmaceutical supply chain. [Garai et al. \(2016\)](#) note the necessity for state interference in the studied processes, as the quality of institutes determines the possibilities for optimization of production planning and distribution in supply chain management.

[Kong and Rönnqvist \(2014\)](#) discuss the importance of coordination of strategic forestry and tactical logistics during production planning in a forestry supply chain. [Xu and Wei \(2013\)](#) describe the increased complexity of production planning and distribution and supply chain management in the construction in a fuzzy environment during realization of large-scale construction projects. [Hashim et al. \(2013\)](#) discuss production planning and supply chain management in a fuzzy environment for large-scale projects of hydropower construction that are also very complex.

[Shin et al. \(2019\)](#) note the necessity for using a two-stage model of perishable reserves for production planning in the food industry. [Petrenko et al. \(2018\)](#) note the influence of production and transaction costs on the results of the activities of modern companies. [Sibirskaya et al. \(2017\)](#) determined the synergetic

effectiveness of investments into the innovative activities of Russian food industry companies. [Ram and Goyal \(2018\)](#) offer a stochastic design for use during production planning and supply chain management. [Panchal et al. \(2018\)](#) performed and presented the results of a risk analysis for ecologically safe and sustainable production in fertilizer manufacturing.

Second direction: analysis of the influence of territorial factors on production planning and supply chain management in industry. Within this direction, different studies on the basis of the practical experience of production planning and supply chain management are performed. The accumulated knowledge in this direction is incomplete, has no system, and requires processing.

According to [Ni and Sun \(2019\)](#), sustainability of supply chain management influences the effectiveness of business and causes positive consequences for integration of the whole supply chain in the production sector of China. [Lim and Sonko \(2019\)](#) discuss the connection between corporate sustainability and innovations in supply chain management in the activities of Taiwanese glass processing companies.

[Singh et al. \(2019\)](#) present an analysis of the factors of adaptation of “green” supply chain management of fertilizer manufacturing in Punjab (India). [Hong et al. \(2019\)](#) describe the influence of the practice and possibilities of supply chain management on exploitation and innovative indicators on the basis of Chinese manufacturers. [Campos et al. \(2019\)](#) describe professional competencies in supply chain management in a medium-sized supermarket in Brazil.

[Tiruneh et al. \(2017\)](#) note the existence of a benefit for efficiency in Africa from R&D in developed countries. [D’Aleo and Sergi \(2017\)](#) note that the human factor is the driving force of formation and keeping of competitive advantages in the logistical sector of EU countries. [Sergi et al. \(2019\)](#) note wide perspectives of financial development of Central Asia and China through cooperation with Russia, due to optimization of chains of production, supply, and sales.

Third direction: studying certain issues of production planning and supply chain management under the conditions of Industry 4.0. Within this direction, perspective (breakthrough) technologies are studied—these could be used in the process of production planning and supply chain management for industry companies, which apply to Industry 4.0.

[Popkova \(2019\)](#) notes the existence of preconditions to the formation and development of Industry 4.0 under the conditions of a knowledge economy. [Popkova et al. \(2019\)](#) offer a perspective model of state management of the economy on the basis of the Internet of Things. [Popkova and Sergi \(2018\)](#) note the strong influence of Industry 4.0 and other innovations on development of the economy (in particular, industry) of modern Russia. [Garina et al. \(2018\)](#) deem it necessary to diversify the approaches to development of industrial production within the context of the development of a complex product. [Mayr et al. \(2019\)](#) discuss the perspectives of the manufacture of electric engines within the context of Industry 4.0.

[Shalini and Kumaravel \(2018\)](#) discuss the development and production of coordinates reconfiguration with the use of flexible robots and machines in

processing within Industry 4.0. Tortorella and Fettermann (2018) offer recommendations for implementing Industry 4.0 and ecologically safe production in Brazilian industrial companies. Khakifirooz et al. (2018) adapt Bayesian inference to the production of semiconductors on the basis of technologies of processing of Big Data for increasing crop yield in intellectual agricultural production on the basis of the opportunities of Industry 4.0.

Moica et al. (2018) describe the changes that should be implemented in shop management for transforming the traditional production system into “Industry 4.0” by the example of car manufacturing for small and medium entrepreneurship. Preuveneers et al. (2017) discuss the necessity for managing identification for cyber-physical production processes and individualized production in Industry 4.0. Hopmann et al. (2017) model maintenance in Industry 4.0 using the example of car parts made of carbon fiber through manufacturing individual repair covers, using geometrically adaptive production forms. Cheng et al. (2016) discuss a project of a production line of a fully automatized company using Industry 4.0. Langer et al. (2016) describe the integration of remote worker in production in Industry 4.0.

Thus, the performed overview of the existing works and publications showed that the economic literature has many examples of refusal of universal models and acknowledgment of the necessity for accounting for the context and specifics of entrepreneurship during production planning and supply chain management. However, most attention is paid to sectorial and regional peculiarities of entrepreneurship, while technological peculiarities (in particular, peculiarities of the fourth technological mode—Industry 4.0) are studied sufficiently.

Thus, there remains uncertainty as to a perspective model of production planning and supply chain management under the conditions of Industry 4.0, which is to be solved by modern economic science. Solving this problem forms a new direction for scientific research (studying technological peculiarities of production planning and supply chain management in industry and their synthesis with known regional peculiarities), within which this chapter has been prepared.

8.3 Materials and method

In this chapter, the authors perform a systemic (qualitative and quantitative) analysis of the regional peculiarities of production planning and supply chain management, which are observed in the modern global economy. The research objects are the following countries (selected according to the criterion of accessibility of statistical information):

- Countries of Western Europe and North America: Germany, France, the United Kingdom, and the United States;
- Countries of Asia, which specialize in industrial production: Japan, South Korea, and China;

- Countries of the CIS (Commonwealth of Independent States) and the EAEU (Eurasian Economic Union): Kazakhstan, Georgia, and Russia.

To compile the regional models of production planning and supply chain management, which are observed in the modern global economy, analysis of the values of statistical indicators is performed. They are grouped into the following seven categories:

1. Marketing

- 12.04 Multistakeholder collaboration, points 1–7 (best): index that is calculated by the experts of the World Economic Forum and presented in the Global Competitiveness Report 2018;
- 12.09 Buyer sophistication, points 1–7 (best): index that is calculated by the experts of the World Economic Forum and presented in the Global Competitiveness Report 2018;
- 11.08 Extent of marketing, points 1–7 (best): index that is calculated by the experts of the World Economic Forum and presented in the Global Competitiveness Report 2017–2018.

2. Innovations

- 12.07 R&D expenditures, % GDP: index that is calculated by the experts of the World Economic Forum and presented in the Global Competitiveness Report 2018;
- 11.05 Attitudes toward entrepreneurial risk, points 1–7 (best): index that is calculated by the experts of the World Economic Forum and presented in the Global Competitiveness Report 2018;
- 11.07 Growth of innovative companies, points 1–7 (best): index that is calculated by the experts of the World Economic Forum and presented in the Global Competitiveness Report 2018;
- 11.08 Companies embracing disruptive ideas, points 1–7 (best): index that is calculated by the experts of the World Economic Forum and presented in the Global Competitiveness Report 2018.

3. Integration

- 12.02 State of cluster development, points 1–7 (best): index that is calculated by the experts of the World Economic Forum and presented in the Global Competitiveness Report 2018.

4. Customs barriers

- 7.01 Distortive effect of taxes and subsidies on competition, points 1–7 (best): index that is calculated by the experts of the World Economic Forum and presented in the Global Competitiveness Report 2018;
- 7.04 Prevalence of nontariff barriers, points 1–7 (best): index that is calculated by the experts of the World Economic Forum and presented in the Global Competitiveness Report 2018;
- 7.05 Trade tariffs, % duty: index that is calculated by the experts of the World Economic Forum and presented in the Global Competitiveness Report 2018;

- 7.06 Complexity of tariffs, points 1–7 (best): index that is calculated by the experts of the World Economic Forum and presented in the Global Competitiveness Report 2018.
- 5. Protection of intellectual property**
 - 12.03 International co-inventions, applications/million population: index that is calculated by the experts of the World Economic Forum and presented in the Global Competitiveness Report 2018;
 - 12.06 Patent applications, applications/million population: index that is calculated by the experts of the World Economic Forum and presented in the Global Competitiveness Report 2018;
 - 12.10 Trademark applications, applications/million population: index that is calculated by the experts of the World Economic Forum and presented in the Global Competitiveness Report 2018;
 - Intellectual property rights, position 1–63 (the lower the better): country's position in the global rating of digital competitiveness, which is determined by the experts of IMD World Competitiveness Center.
- 6. Market concentration**
 - Extent of market dominance, points 1–7 (best): index that is calculated by the experts of the World Economic Forum and presented in the Global Competitiveness Report 2018.
- 7. Added-value chains**
 - 11.05 Value chain breadth, points 1–7 (best): index that is calculated by the experts of the World Economic Forum and presented in the Global Competitiveness Report 2017–2018;
 - 11.06 Control of international distribution, points 1–7 (best): index that is calculated by the experts of the World Economic Forum and presented in the Global Competitiveness Report 2017–2018;
 - 11.07 Production process sophistication, points 1–7 (best): index that is calculated by the experts of the World Economic Forum and presented in the Global Competitiveness Report 2017–2018.

The numbers of the above indicators (e.g., 12.04., 12.09, etc.) are assigned by the experts of the international statistical and analytical organizations and are used in their reports, for example, the Global Competitiveness Report. In this research, the indicators with their numbers are given—so that readers can check the correctness of the used data and find them in the international reports.

The indicators that are measured in points (compatible measuring units) are used for compilation of regions' profiles and preliminary calculation of direct averages of the values of the indicators in each region's countries. The obtained profiles are compared with the help of the method of comparative analysis. Then, qualitative analysis of the determined regional peculiarities in view of the modern practical experience of production planning and supply chain management in the selected countries is performed. Based on the results of the analysis, structural and logical (qualitative) regional models are compiled, which explain the

economic sense of the determined quantitative (in the values of statistical indicators) differences.

Also, correlation and regression analysis of the influence of the above indicators of production planning and supply chain management on the indicators of development of Industry 4.0 is performed: the share of medium-tech and hi-tech productions in the structure of added value in industry and share of export of hi-tech products in the structure of export, according to experts of the World Bank. Coefficients of autocorrelation (R^2) and regression curves of the most significant ($R^2 \geq 0.5$) correlation dependencies are built. The statistical basis of the research is shown in [Tables 8.1 and 8.2](#).

8.4 Results

8.4.1 Regional models of production planning and supply chain management in the modern global economy

Based on the calculated direct average, we compiled quantitative profiles of regional models of production planning and supply chain management in the modern global economy ([Figs. 8.1–8.3](#)). During compilation of these diagrams, only indicators in points are taken into account for ensuring data compatibility, therefore variables x_5 , x_9 , x_{15} , x_{17} , x_{18} , and x_{20} are absent.

As is shown in [Fig. 8.1](#), the specific features of the European/American model of production planning and supply chain management are increased customs barriers (low values of x_6 and x_{10}), high marketing (increased value of x_{16}), innovative (increased value of x_4) activity, and reduced added-value chains (increased value of x_3).

As is shown in [Fig. 8.2](#), the specific features of the Asian model of production planning and supply chain management are reduced marketing activity (low value of x_{13}), high customs barriers (increased value x_6), and reduced added-value chains (increased value of x_1).

As is shown in [Fig. 8.3](#), the specific features of the Eurasian model of production planning and supply chain management are high level of markets monopolization (reduced value of x_7) and high customs barriers (increased value of x_6).

As is shown in [Fig. 8.4](#), in the European/American model of production planning and supply chain management, only the main company is located in the region of location. It deals with marketing and innovations and controls the supply chains (coordinates the actions of all its branches). As a result of marketing research, the needs for the company's products are determined and perspective innovative technologies for their complete and effective satisfaction are developed.

The finished technologies and strategic priorities are passed to production departments. In their turn, they conduct production planning. Finished products are sold in the region of production and are supplied directly by the manufacturers

Table 8.1 Statistical basis of the research for 2018 (part 1)

Model	Country	Share of medium-tech and hi-tech productions	Share of export of hi-tech products	11.05	11.06	11.07	11.08	Protection of intellectual property
		y ₁	y ₂	From the report for 2017–20118				x ₅
European and American model	Germany	0.60	14	5.6	5.5	5.9	5.5	5
	France	0.48	24	5.4	5.1	5.6	5.4	10
	United Kingdom	0.48	21	5.6	5.3	5.9	5.8	7
	United States	0.47	14	5.7	5.7	5.9	6.0	9
	Average	0.51	18.25	5.58	5.40	5.83	5.68	7.75
Asian model	Japan	0.55	14	6.1	5.4	6.4	5.1	21
	South Korea	0.63	14	4.9	5.2	5.2	4.8	39
	China	0.41	26	4.5	4.4	4.5	4.6	42
Eurasian model	Average	0.53	18.00	5.17	5.00	5.37	4.83	34.00
	Kazakhstan	0.16	23	3.1	3.2	3.6	4.1	41
	Georgia	0.18	3	3.8	3.4	3.5	4.2	-
	Russia	0.26	12	3.8	3.7	3.9	4.5	52
	Average	0.20	12.67	3.57	3.43	3.67	4.27	46.50

Compiled and calculated by the authors based on IMD World competitiveness center, [2019](https://www.imd.org/wcc/world-competitiveness-center-rankings/world-digital-competitiveness-rankings-2018/). World digital competitiveness ranking 2018. Available from: <https://www.imd.org/wcc/world-competitiveness-center-rankings/world-digital-competitiveness-rankings-2018/> (accessed 24.06.19.), World Bank, [2019a](https://data.worldbank.org/indicator/TX.VAL.TECH.MF.ZS?view=chart). High-technology exports (% of manufactured exports). Available from: <https://data.worldbank.org/indicator/TX.VAL.TECH.MF.ZS?view=chart> (accessed 24.06.19.), World Bank, [2019b](https://tcddata360.worldbank.org/indicators/hbe238413?country=BRA&indicator=3794&viz=line_chart&years=1990,2014). Medium- and high-tech manufacturing value added share in total manufacturing value added. Available from: https://tcddata360.worldbank.org/indicators/hbe238413?country=BRA&indicator=3794&viz=line_chart&years=1990,2014 (accessed 24.06.19.), World Economic Forum, [2019b](http://www3.weforum.org/docs/GCR2017-2018/05FullReport/TheGlobalCompetitivenessReport2017-2018.pdf). The Global Competitiveness Report 2017–2018. Available from: <http://www3.weforum.org/docs/GCR2017-2018/05FullReport/TheGlobalCompetitivenessReport2017-2018.pdf> (accessed 24.06.19.).

Table 8.2 Statistical basis of the research for 2018 (part 2, from the report for 2018).

Model	Country	7.01 x ₆	7.02 x ₇	7.04 x ₈	7.05 x ₉	7.06 x ₁₀	11.05 x ₁₁	11.07 x ₁₂	11.08 x ₁₃	12.02 x ₁₄	12.03 x ₁₅	12.04 x ₁₆	12.06 x ₁₇	12.07 x ₁₈	12.09 x ₁₉	12.10 x ₂₀
European and American model	Germany	5.0	5.5	5.1	1.13	3.0	5.1	5.4	5.0	5.5	21.26	5.4	295.32	2.9	5.0	8457.38
	France	4.5	4.4	4.2	1.13	3.0	3.8	4.3	3.8	4.8	1.59	4.2	144.66	2.2	4.0	5542.72
	United Kingdom	4.6	4.8	5.2	1.13	3.0	5.1	5.2	4.7	5.2	12.47	5.1	100.63	1.7	4.7	6667.07
	United States	5.1	5.7	5.3	1.66	3.7	5.8	5.8	5.7	5.8	12.30	5.8	144.09	2.8	5.6	2890.49
	Average	4.80	5.10	4.95	1.26	3.18	4.95	5.18	4.80	5.33	11.91	5.13	171.18	2.40	4.83	5889.42
Asian model	Japan	4.8	5.9	4.9	2.05	4.2	4.2	5.0	3.9	5.3	5.39	4.8	496.46	3.3	4.9	1814.71
	South Korea	3.8	3.5	4.4	9.04	4.9	3.9	4.5	3.9	4.6	15.46	4.3	444.63	4.2	5.3	4378.73
	China	4.1	4.5	4.5	12.19	6.4	4.5	4.4	4.2	4.6	0.99	4.4	12.28	2.1	4.5	1561.67
	Average	4.23	4.63	4.60	7.76	5.17	4.20	4.63	4.00	4.83	7.28	4.50	317.79	3.20	4.90	2585.04
	Kazakhstan	4.2	3.6	4.5	4.43	4.3	4.8	3.6	3.6	3.1	0.09	3.7	0.39	0.2	3.7	183.00
Eurasian model	Georgia	4.4	3.6	4.9	0.92	4.4	4.1	3.6	3.6	3.1	0.24	3.3	0.60	0.3	3.2	510.00
	Russia	3.6	3.7	3.9	4.57	3.4	4.3	3.7	3.6	3.5	0.75	4.0	479.0	1.1	3.5	197.29
	Average	4.07	3.63	4.43	3.31	4.03	4.40	3.63	3.60	3.23	0.36	3.67	160.00	0.53	3.47	296.76

Compiled and calculated by the authors based on World Economic Forum, 2019a. The Global Competitiveness Report 2018. Available from: <http://www3.weforum.org/docs/GCR2018/05FullReport/TheGlobalCompetitivenessReport2018.pdf> (accessed 24.06.19.).

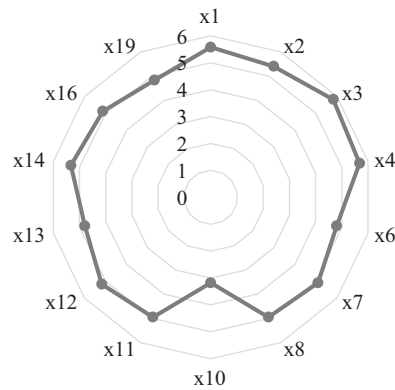


FIGURE 8.1 Profile of the European/American model of production planning and supply chain management.

Calculated and built by the authors.

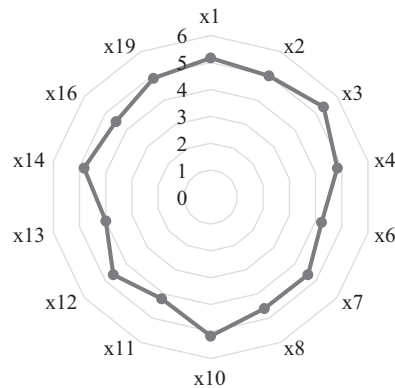


FIGURE 8.2 Profile of the Asian model of production planning and supply chain management.

Calculated and built by the authors.

(without the participation of the main company) to the region (or several regions) of sales, in which additional production could be started. This ensures increased flexibility of production planning and supply chain management

As is shown in Fig. 8.5, in the Asian model of production planning and supply chain management the company borrows experience from successful rivals in the region of location. The rivals deal with marketing and innovations, and the company officially (purchasing the rights for the objects of intellectual property) and unofficially (with possible violation of rights for the objects of intellectual property—this practice is popular in China) “copies” their results and uses them.

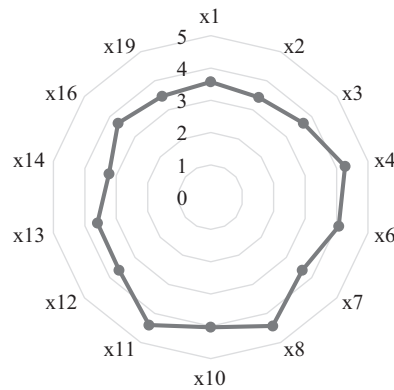


FIGURE 8.3 Profile of the Eurasian model of production planning and supply chain management.

Calculated and built by the authors.

Production planning and supply chain management are conducted by one company, which deals with mass production for obtaining the “scale effect.” Then finished products are sold in several sales regions. This model allows guaranteeing low prices, but does not ensure high quality of manufactured and sold products—which often hinders the sales.

As is shown in Fig. 8.6, in the Eurasian model of production planning and supply chain management is an important role that belongs to the state. It places a preliminary order for the products in order to guarantee jobs and stimulate business activity in the economy. Production companies are integrated in a long chain of added value and supply intermediary products to each other. Their close interconnection hinders the implementation of innovations, as they should be implemented by all companies in the added-value chains. As a result, final products are passed to the state and consumers. Only the final company conducts marketing activities.

Thus, the determined regional models of production planning and supply chain management differ from each other as to all distinguished criteria of comparison (marketing, innovations, integration, customs barriers, protection of intellectual property, market concentration, and added-value chains). Then it is necessary to determine how these models are fit for production planning and supply chain management under the conditions of Industry 4.0.

8.4.2 Perspective model of production planning and supply chain management under the conditions of Industry 4.0

The results of the performed correlation analysis are shown in Fig. 8.7.

As can be seen from Fig. 8.7, the most significant ($R^2 \geq 0.5$) correlation dependencies are as follows:

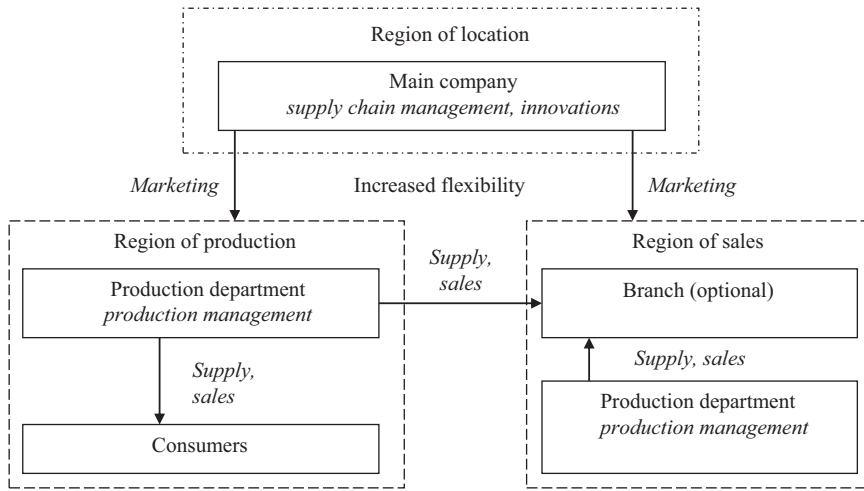


FIGURE 8.4 European and American structural and logical model of production planning and supply chain management.

Compiled and built by the authors.

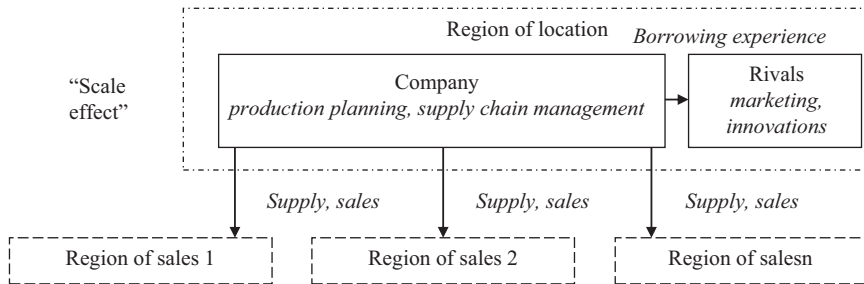


FIGURE 8.5 The Asian structural and logical model of production planning and supply chain management.

Compiled and built by the authors.

- Connection between the share of medium-tech and hi-tech productions and indicator 11.05 Value chain breadth: $y1x1$ ($R^2 = 0.86$);
- Connection between the share of medium-tech and hi-tech productions and indicator 11.07 Production process sophistication: $y1x3$ ($R^2 = 0.88$);
- Connection between the share of medium-tech and hi-tech productions and indicator 11.08 Extent of marketing: $y1x4$ ($R^2 = 0.69$);
- Connection between the share of export of hi-tech products and the indicator of protection of intellectual property $y2x5$ ($R^2 = -0.56$);
- Connection between the share of medium-tech and hi-tech productions and indicator 7.02 Extent of market dominance: $y1x7$ ($R^2 = 0.57$);

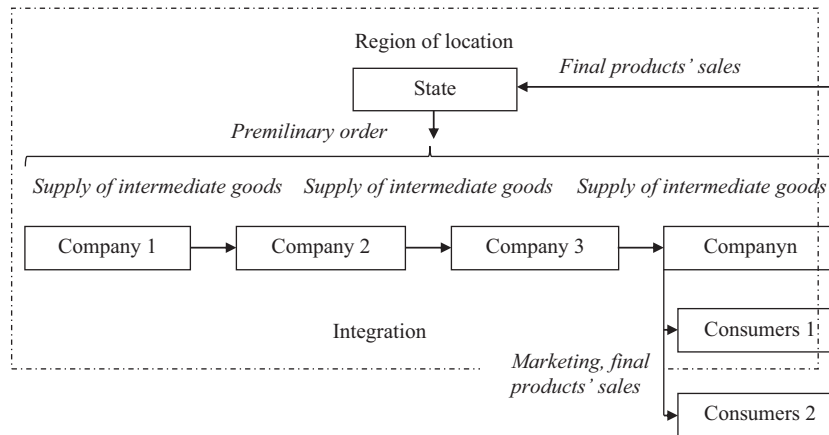


FIGURE 8.6 The Eurasian structural seven logical model of production planning and supply chain management.

Compiled and built by the authors.

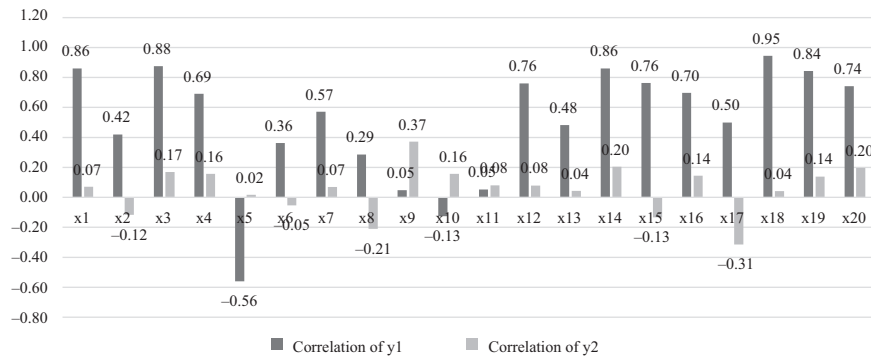


FIGURE 8.7 Coefficients of correlation.

Calculated and built by the authors.

- Connection between the share of medium-tech and hi-tech productions and indicator 11.07 Growth of innovative companies: $y1x12$ ($R^2 = 0.76$);
- Connection between the share of medium-tech and hi-tech productions and indicator 12.02 State of cluster development: $y1x14$ ($R^2 = 0.86$);
- Connection between the share of medium-tech and hi-tech productions and indicator 12.03 International co-inventions: $y1x15$ ($R^2 = 0.76$);
- Connection between the share of medium-tech and hi-tech productions and indicator 12.04 Multistakeholder collaboration: $y1x16$ ($R^2 = 0.70$);
- Connection between the share of medium-tech and hi-tech productions and indicator 12.07 R&D expenditures: $y1x18$ ($R^2 = 0.95$);

- Connection between the share of medium-tech and hi-tech productions and indicator 12.09 Buyer sophistication: $y1x19$ ($R^2 = 0.84$);
- Connection between the share of medium-tech and hi-tech productions and indicator 12.10 Trademark applications: $y1x20$ ($R^2 = 0.74$).

Regression curves that characterize the selected dependencies are shown in Fig. 8.8.

Fig. 8.8 shown that an increase of $x1$ (11.05 Value chain breadth) by 1 point leads to an increase of medium-tech and hi-tech production by 0.1435% in the

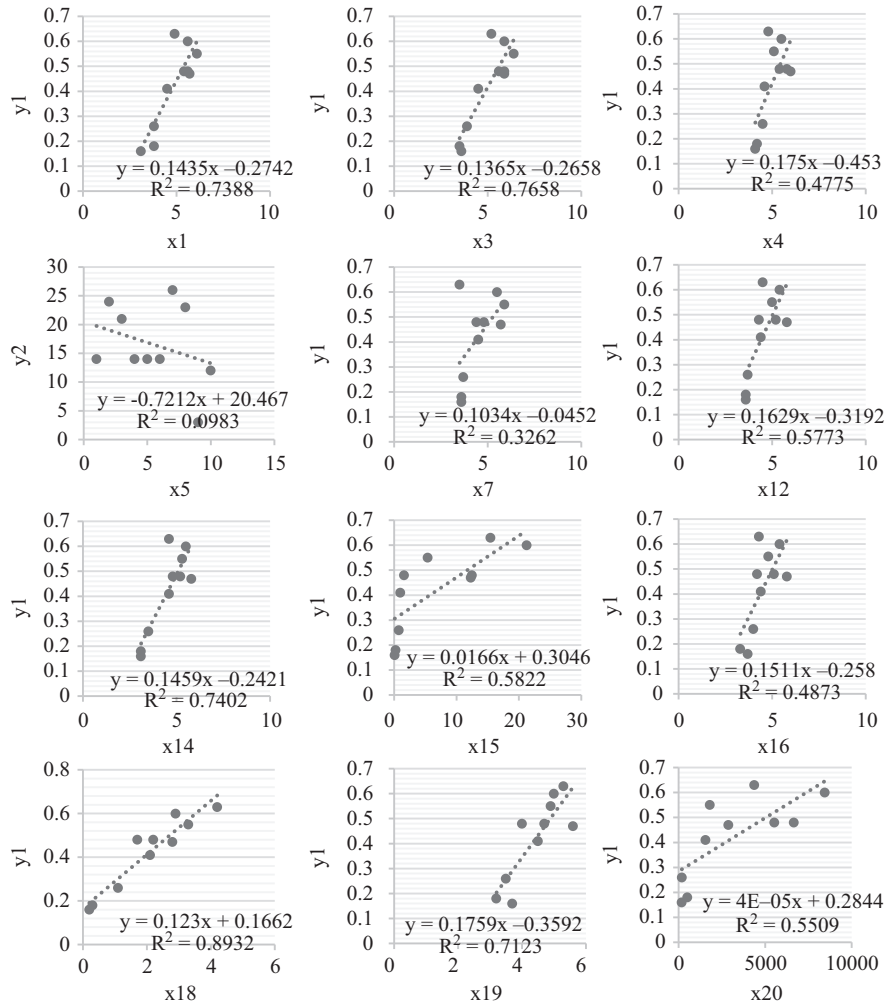


FIGURE 8.8 Regression curves that show the influence of the selected indicators of production planning and supply chain management on the indicators of development of Industry 4.0.

Calculated and built by the authors.

structure of added value in industry. An increase of x3 (11.07 Production process sophistication) by 1 point leads to an increase of medium-tech and hi-tech production by 0.1365% in the structure of added value in industry. An increase of x4 (11.08 Extent of marketing) by 1 point leads to increase of medium-tech and hi-tech production by 0.1750% in the structure of added value in industry.

An increase of x5 (Intellectual property rights) by 1 position leads to a reduction of the volume of export of hi-tech products by 0.7212% in the structure of export. An increase of x7 (7.02 Extent of market dominance) by 1 point leads to an increase of medium-tech and hi-tech production by 0.1034% in the structure of added value in industry. An increase of x12 (11.07 Growth of innovative companies) by 1 point leads to an increase of medium-tech and hi-tech production by 0.1629% in the structure of added value in industry.

An increase of x14 (12.02 State of cluster development) by 1 point leads to an increase of medium-tech and hi-tech production by 0.1459% in the structure of added value in industry. An increase of x15 (12.03 International co-inventions) by 1 point leads to an increase of medium-tech and hi-tech production by 0.0166% in the structure of added value in industry. An increase of x16 (12.04 Multi-stakeholder collaboration) by 1 point leads to an increase of medium-tech and hi-tech production by 0.1511% in the structure of added value in industry.

An increase of x18 (12.07 R&D expenditures) by 1% of GDP leads to an increase of medium-tech and hi-tech production by 0.1230% in the structure of added value in industry. An increase of x19 (12.09 Buyer sophistication) by 1 point leads to an increase of medium-tech and hi-tech production by 0.1759% in the structure of added value in industry. An increase of x20 (12.10 Trademark applications) by 1 application/million population leads to an increase of medium-tech and hi-tech production by 4E-0.5% ($\rightarrow 0$) in the structure of added value in industry.

Therefore the development of Industry 4.0 is stimulated by a decrease of added-value chains and marketing and innovative activity and integration. The development of Industry 4.0 is restrained by protection of intellectual property and competition. These results are contradictory—they are to be clarified by comparative analysis of the regional models of production planning and supply chain management in the modern global economy between each other and as to the criterion of applicability under the conditions of Industry 4.0 (Table 8.3).

As is shown in Table 8.3, neither of the existing regional models of production planning and supply chain management in the modern global economy could be applied under the conditions of Industry 4.0, although the European and American model is the closest to an applicable model. All the existing regional models envisage direct marketing—preliminary research of the market and post-production promotion and sales of products (logistics “just-in-case”). Under the conditions of Industry 4.0, orders are collected and then production is planned and conducted (logistics “just-in-time”). Under the conditions of Industry 4.0, important roles belong to high innovative activity, strong protection of intellectual property, and short added-value chains. The developed perspective model of production planning and supply chain management under the conditions of Industry 4.0 is shown in Fig. 8.9.

Table 8.3 Comparative analysis of regional models production planning and supply chain management in the modern global economy between each other and as to the criterion of applicability under the conditions of Industry 4.0

Criteria of comparison	European and American model	Asian model	Eurasian model	Industry 4.0
Marketing	Strong, direct	Weak, direct	Weak, direct	Strong, bilateral
Innovations	Strong	Moderate	Weak	Strong
Integration	Weak	Weak	Strong	Weak
Logistics	“Just-in-case”			“Just-in-time”
Customs barriers	High	Low	High	Any
Protection of intellectual property	Strong	Weak	Moderate	Strong
Market structure	Competition	Competition	Monopoly	Any
Added-value chains	Short	Moderate	Long	Short

Developed and compiled by the authors.

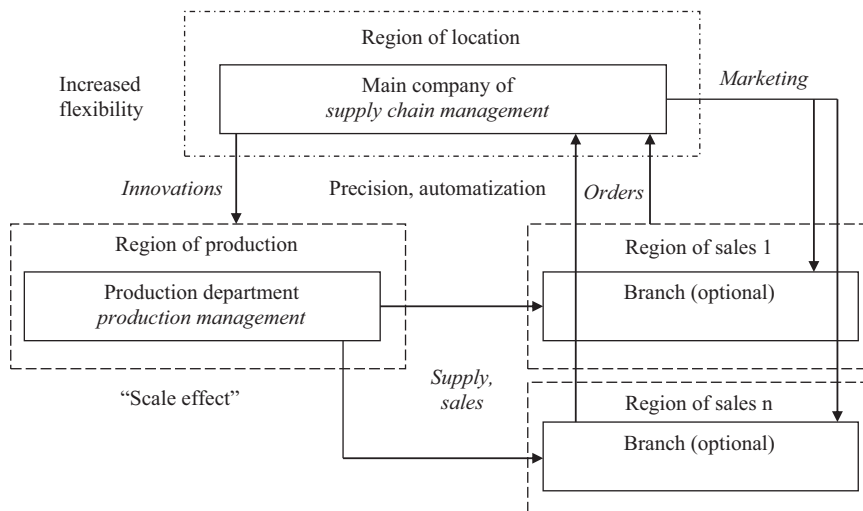


FIGURE 8.9 Model of production planning and supply chain management under the conditions of Industry 4.0.

Compiled and built by the authors.

Fig. 8.9 shows that, under the conditions of Industry 4.0, the main company conducts preliminary marketing research and promotes its products in the regions of sales. It collects orders from all consumers and plans production and supply and sales chains for obtaining the “scale effect.” The developed technologies and

plans of production are passed to the production department (or several departments) in the regions of production (to reduce costs). Final products are passed to the company's branches in the regions of sales or directly to consumers.

8.4.3 Adapting the perspective model of production planning and supply chain management under the conditions of Industry 4.0 to the specifics of regions of the world

The developed perspective model of production planning and supply chain management under the conditions of Industry 4.0 could be specified and changes are necessary, in view of the regional peculiarities of its practical application—under the condition of preservation of its main characteristics. In the countries of Western Europe and America, the model of production planning and supply chain management under the conditions of Industry 4.0 could be adapted to the specifics of regional entrepreneurship through the creation of production departments in the regions of product sales and provision of a high level of their economic independence (own production planning under the condition of obtaining the “scale effect”).

In Asian countries, the model of production planning and supply chain management under the conditions of Industry 4.0 could be adapted to the specifics of regional entrepreneurship through translating technologies in the economy. Though under the conditions of Industry 4.0 a high level of protection of intellectual property is offered, this condition could vary depending on the context. For example, conducting marketing research and development of innovations by independent organizations (e.g., specialized expert and marketing agencies, R&D institutes, and the state) allows for mass distribution of the obtained results with the protection of intellectual property.

In the countries of Eurasia (the CIS and the EAEU), the model of production planning and supply chain management under the conditions of Industry 4.0 could be adapted to the specifics of regional entrepreneurship through increased integration. Though Industry 4.0 envisages short added-value chains, it is possible to allow for an integrated production process under the condition of cooperation of the participating companies and a high rate of production.

8.5 Conclusions

Thus, the results of the performed research showed that three regional models of production planning and supply chain management exist in modern global economic practice. The European and American model, which is implemented in the countries of Western Europe and North America (e.g., Germany, France, the United Kingdom, and the United States), envisages foundation on the marketing and innovative activities of companies in industry; the model is oriented at a

highly competitive market environment and short added-value chains. It is very close to the model of Industry 4.0.

The Asian model, which is used in the industrial countries of Asia (e.g., Japan, South Korea, and China), envisages obtaining the “scale effect” and is oriented at weak protection of intellectual property and low customs barriers. The Eurasian model, which is used in the CIS and the EAEU (e.g., Kazakhstan, Georgia, and Russia), envisages integration of companies into long added-value chains; it is oriented at the market structure of monopoly, preliminary state order with weak marketing, and limited opportunities for companies’ innovative activities.

The model of production planning and supply chain management, which is developed in this work for Industry 4.0, envisages active bilateral (promotion and collection of orders from consumers) marketing, high innovative activity, logistics “just-in-time” (production in the course of receipt of orders with minimum storage reserves), protection of intellectual property, and short added-value chains (maximum proximity of manufacturers and consumers and their direct interaction). The offered model could be applied to the activities of companies from any region or sphere, but it requires deep transformations in the practice of production planning and supply chain management.

Unlike other existing research and publications on the topic of Industry 4.0, in which emphasis is made on perspective (breakthrough) technologies and their adaptation to production planning and supply chain management under the conditions of Industry 4.0, in this chapter we pay attention to the organizational issues. This research has shown that regardless of the technologies that are used during production planning and supply chain management, the regional context determines the specifics of the organization of this process. Under the conditions of Industry 4.0, it is different not only due to novelty of the applied technologies but also due to special organization. That is why transition of modern companies to Industry 4.0 should be accompanied not only by purchase and implementation of breakthrough technologies but also by modernization of the system of production planning and supply chain management.

It should be noted that apart from the already-formed three regional models of production planning and supply chain management, other regional models are also being institutionalized (e.g., the African model, realized in the industrial countries of Africa). These models also require elaboration and management, which should be aimed not at the correction of already-formed social institutes but at management of the processes of formation of social institutes and support for their flexibility, as well as adaptation to the conditions of Industry 4.0.

Acknowledgment

The research has been performed with financial support from the Russian Foundation of Fundamental Research within scientific project No. 18-010-00103 A.

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Infrastructural provision and organization of production on the basis of the Internet of Things

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9.1 Introduction

The Internet is such a popular technology now that it is possible to state the formation of the Internet economy—an economic system in which the Internet is used in most socioeconomic processes, connections, and relations. A large share of interpersonal communications (e.g., communication in social networks) and a large share of distributive processes in entrepreneurship (online marketing and sales, online financial operations) take place on the basis of Internet technologies; state services are provided and state regulation of economy (e-government) are also performed on the basis of Internet technologies.

The Fourth Industrial Revolution (transition to Industry 4.0) is to become a new stage in the development of the Internet economy, at which mass implementation of a breakthrough digital technology—the Internet of Things—will take place. The perspectives of practical application of this technology are very wide. One of the directions is development of the consumer society and an increase in its inclusiveness. Mass distribution of the Internet of Things among consumers might ensure a quick leap of popularity for online trade. Consumers will be able to apply for satisfaction of certain needs or for specific goods and set the criteria of selection of the most optimal ones; devices that are connected to the Internet will automatically select goods and make purchases. Also, long-term balance will be set in the commodity markets.

Another direction is connected to usage of “machine vision” during formation of “smart territories.” Digital devices, which are connected to the Internet, on the whole territory (e.g., city or region) send photo, audio, and video information to the state server, where artificial intelligence (AI) determines target economic operations (e.g., “shadow” entrepreneurship, change of consumer preferences, etc.). However, the most promising and attractive direction (in terms of investments) is the one within which the Internet of Things is used in production processes in entrepreneurship, ensuring a range of advantages.

First, the very name “Internet of Things” implies that it envisages interobject communication (without participation of subjects—i.e., humans). Digital devices interact with the help of the Internet, which allows eliminating of the influence of the “human factor” on the production processes, thus guaranteeing rational decision-making. Unlike humans, each of which possesses personal features and requires an individual approach to management (e.g., necessity for stimulation of labor and complexity of team-building), digital devices are impersonal—their management is impersonal, simplified, and standardized.

Second, the Internet of Things envisages continuity of communications of digital devices and constant monitoring and control of their work by AI. This allows for timely determination of the need for technical maintenance and repairs, avoiding failures and termination of production. For this reason, the risk of violation of production rates and supply of final products is reduced, and expenditures for fixed assets (technical maintenance, as a rule, is cheaper than replacing the

components and purchase of new devices) are decreased. This allows for precise calculation and bringing down to the minimum of the volume of consumed resources and production waste.

Third, digital devices are integrated into the common network with the help of the Internet of Things. This allows determining “strong” and “weak” spots in the company’s activities and controlling them, as well as planning production with complete accounting of all capabilities of the company. Expanded capabilities of analytics allow for precise forecasting of the company’s development and prevention of the crises of its activities. System integration of all devices of the company on the basis of the Internet of Things can create a synergetic effect in the form of growth of efficiency and maximization of “advantages from scale.”

Despite the stated advantages of using the Internet of Things in entrepreneurship and high investment attractiveness of the projects on its implementation, it is restrained by uncertainty of the process of production on the basis of the Internet of Things. While the basic principles of this process are widely known (automatization, rationality, constant intellectual analysis and control, and integration), the conceptual basis of its organization is not yet formed. Apart from this, the requirements for infrastructural provision and its sufficiency in the modern economic systems are unclear. This does not allow assessing their readiness for formation of entrepreneurship of Industry 4.0.

In this work, we offer hypothesis H_{01} —infrastructural provision is very important in development of entrepreneurship of Industry 4.0 and, in particular, in organization of production on the basis of the Internet of Things. We also offer hypothesis H_{02} —in the modern economic systems (countries of the world) there is a deficit of infrastructural provision of entrepreneurship of Industry 4.0, which does not allow starting mass organization of production on the basis of the Internet of Things.

Accordingly, the purpose of this research is to verify the offered hypotheses through studying the infrastructural provision and organization of production on the basis of the Internet of Things. To achieve this goal, we determine the essence and specific features of the Fourth Industrial Revolution and the advantages of automatized production on the basis of the Internet of Things; perform modeling of production and distribution processes in the Internet economy during automatized production on the basis of the Internet of Things; and determine the specific features, deficit, and perspectives of overcoming the deficit of infrastructural provision of automatized production on the basis of the Internet of Things in modern economic systems.

9.2 Literature review

The scientific and theoretical basis of the research consists of new scientific works in which the following issues are elaborated. first issue: essence of transition of the modern economic systems to Industry 4.0 in the process of the Fourth Industrial

Revolution, its specifics as compared to previous industrial revolutions. [Onik et al. \(2019\)](#) note that in the conditions of the Fourth Industrial Revolution the problem of confidentiality of personal data and corporate information, which are a commercial secret, increases. [Loureiro \(2018\)](#) writes that as the Fourth Industrial Revolution is based on digital technologies, it is actually a digital revolution.

[Alimkhan et al. \(2019\)](#) also note that the Fourth Industrial Revolution is not limited by industry and, in particular, covers the fuel and energy complex—scholars study this by the example of the energy sphere 4.0 in Kazakhstan. [Gotesman Bercovici et al. \(2019\)](#) point out that the Fourth Industrial Revolution influences the Israeli economy, which is post-industrial—which proves the universal character of the revolution and the systemic character of consequences of transition to the fourth technological mode (Industry 4.0).

[Ayentimi and Burgess \(2019\)](#) dwell on the volume of coverage of the Fourth Industrial Revolution and come to the conclusion on its comprehensive influence, which covers the countries of sub-Saharan Africa. [Popkova \(2019\)](#) dwells on the preconditions to formation and development of Industry 4.0 in the conditions of the knowledge economy. [Popkova and Sergi \(2019\)](#) substantiate that Industry 4.0 as a revolutionary tendency of innovative development of the modern economy influences developed and developing countries (by the example of Russia).

Second issue: formation, functioning, management, and development of the Internet economy, as well as conducting entrepreneurship in it. The scientific and methodological basis of the Internet economy are developed in the work by [Sukhodolov et al. \(2018a\)](#). [Sukhodolov et al. \(2018b\)](#) describe the perspectives of creation of the Internet economy. [Sukhodolov et al. \(2018c\)](#) reflect on the micro-economic aspect of functioning and development of the Internet economy, noting the formation of a new type of entrepreneurship—Internet entrepreneurship—which conducts economic activities in the Internet.

[Petrenko et al. \(2018\)](#) study the issue of sustainable development of the economy. Its solution is seen by the authors in modernization of the service sphere in the postindustrial economy via development of online trade. [Calzada and Tselekounis \(2018\)](#) note lengthening of the added-value chain in the Internet economy, which is called by them “unproductive” (there is no production, only trade is developing). [Schneider \(2018\)](#) calls the Internet economy the “online economy,” emphasizing one of its key advantages—the possibility of improving the economic operations any place any time under the condition of access to the Internet.

[Chang and Dai \(2018\)](#) emphasize the priority of marketing in the Internet economy as a driving force of online (Internet) trade. [Long \(2017\)](#) presents the results of research of competitive strategies of online commerce companies in the Internet economy and comes to the conclusion that strategies are largely determined by the technological mode (shown by the example of differences in the Internet—high speed, broadband, etc.).

Third issue: perspectives of using the Internet of Things in the production processes in entrepreneurship. [Popkova et al. \(2019\)](#) offer a perspective model of

state management of economy on the basis of the Internet of Things. Cecil et al. (2019) compile a platform of cyber-production on the basis of the Internet of Things for the assembly of microdevices. Patel et al. (2019) emphasize an important role of robotronics in the sphere of production, energy, goods, and transport in the paradigm of the Internet of Things.

Song et al. (2019) emphasize the necessity for managing the sustainability of the social Internet of Things for producing customized industrial goods. Ciampi and Rialti (2019) note the high complexity of management in science-driven production companies in the age of Big Data and the importance of the Internet of Things and AI. Yang et al. (2019) write that the Internet of Things occupies the central place in “smart” production.

Technical publications on the topic of the Internet of Things also deserve attention. Kryvenchuk et al. (2019) describe an intellectual integration robotronic system for small and medium-sized companies, which is controlled by the Internet of Things and based on dynamic production processes. Jung et al. (2019) offer technical solutions for designing the systems of maintenance of production premises on the basis of the Internet of Things. Goyal et al. (2017) offer a new scientific and methodological approach to evaluating the efficiency of an autonomous robot with the help of Rework. Rawat et al. (2017) perform modeling of growth of reliability of software for developing flexible software, which is in high demand in cyber-physical systems, which include the Internet of Things.

Fourth issue: structure of infrastructural provision of Industry 4.0 and the level of its development in modern economic systems. Morozova et al. (2019) note that sustainable development of global entrepreneurship is based on infrastructural provision, which has to take into account the current needs of entrepreneurial structure, which grow in the conditions of Industry 4.0. MacAk et al. (2017) perform an evaluation of the similarity between modeled behavior and the factual product from economic and technical points of view depending on the infrastructural provision in the conditions of Industry 4.0. Winseck (2017) presents the geopolitical economy of the global Internet infrastructure.

Świątek (2019) points out a significant difference between the treated and factual essence of Industry 4.0 and the planned and real needs of companies of Industry 4.0 for infrastructural provision of their activities. Sándor et al. (2018) write about the importance of infrastructure for the development of entrepreneurship of Industry 4.0. Wallis et al. (2017) present the result of the performed adaptation of management of privileged (elite) infrastructure to specifics of Industry 4.0. Hammer et al. (2017) think that profit per unit of time (e.g., 1 hour) should be a target parameter for managing the process for the production systems, which are supported by analytics of Big Data and the infrastructure of Industry 4.0.

The performed content analysis of the existing research and publications that are devoted to the studied issues, determined the high level of their elaboration. At the same time it is established that the concept of organization of production on the basis of the Internet of Things is being formed, due to which the systemic

vision of this organization is absent. The scientific data on infrastructural provision of entrepreneurship in the conditions of Industry 4.0 and, in particular, organization of production on the basis of the Internet of Things are scattered and need to be specified. These gaps are to be filled by the presented research.

9.3 Materials and method

For verification of hypothesis H_{01} , Pearson's chi-squared test (χ^2) is used. With the help of criterion χ^2 we perform an evaluation of the statistical significance of the differences between variation of the level of development of the infrastructure components and the number of robots per 10,000 workers in industry. For this, we compile a contingency table; in this research, calculations are complicated by a large number of fields (more than four) of the contingency table for obtaining precise and authentic results (Table 9.1).

In Table 9.1 O_{ij} , the crossing of columns and lines, is the number of observations, which corresponds to criteria i and j —that is, in the set interval of the number of robots per 10,000 workers in industry and characterized by the corresponding variation of the level of development of infrastructure components. The observed value χ^2 (χ^2_{obs}) is calculated with the help of the following formula (adapted to this research):

$$\chi^2_{\text{obs}} = \frac{\sum_{i=1,m} \sum_{j=1,2} (\sum i - O_{ij})^2}{O_{ij}} \quad (9.1)$$

According to formula (9.1), the sum of ratios of squares of difference of the total number of observations in the line and the target number of observations (with variation that is below 15%) to the target number of observations found. Table value χ^2 is calculated with the help of a standard formula in Microsoft Excel: $\chi^2_{\text{table}} = \text{CHI2.OBP}(\alpha; f)$, where α is the level of significance (in this research, let us adopt the level of significance 0.95, at which error does not exceed 5%); f is the number of levels of freedom, which is calculated according to formula: $f = (i-1) \times (j-1)$, where i is the number of columns and j is the number of lines. If $\chi^2_{\text{obs}} > \chi^2_{\text{table}}$, the offered hypothesis H_{01} is proved.

For determining the intervals of the number of robots per 10,000 workers in industry we use Sturges' rule:

$$Q = 1 + 3.322 \times \ln N \quad (9.2)$$

where Q is the number of intervals in which the selection is to be divided; and N is the number of observations in the selection.

Limits of intervals are determined with the help of the following formula:

$$h = \frac{(x_{\text{max}} - x_{\text{min}})}{N} \quad (9.3)$$

Table 9.1 The model of a multifield contingency table, which is used for verification of hypothesis H_{01} with the help of Pearson's chi-squared test (χ^2).

Intervals of the number of robots per 10,000 workers in industry	Variation of the level of development of infrastructure components		Sums for lines ($\sum i$)	Probability of the selection's element being in the studied interval (P_i), %
	Below 15% (j_1)	Above 15% (j_2)		
$[i_1-i_2)$	$O_{i_1-2j_1}$	$O_{i_1-2j_2}$	$\sum i_{1-2} = O_{i_1-2j_1} + O_{i_1-2j_2}$	$P_{i_1-2} = \sum i_{1-2} / \sum ij$
$[i_2-i_3)$	$O_{i_2-3j_1}$	$O_{i_2-3j_2}$	$\sum i_{2-3} = O_{i_2-3j_1} + O_{i_2-3j_2}$	$P_{i_2-3} = \sum i_{2-3} / \sum ij$
...	...	...	...	...
$[i_n-i_m]$	$O_{i_n-mj_1}$	$O_{i_n-mj_2}$	$\sum i_{n-m} = O_{i_n-mj_1} + O_{i_n-mj_2}$	$P_{i_n-m} = \sum i_{n-m} / \sum ij$
Sums for columns ($\sum j$)	$\sum j_1 = O_{i_1-2j_1} + O_{i_2-3j_1} + \dots + O_{i_n-mj_1}$	$\sum j_2 = O_{i_1-2j_2} + O_{i_2-3j_2} + \dots + O_{i_n-mj_2}$	$\sum ij = \sum i_{1-2} + \sum i_{2-3} + \sum i_{n-m} = \sum j_1 + \sum j_2$	—
Probability of the selection's element being characterized by the set variation (P_j), %	$P_{j_1} = \sum j_1 / \sum ij$	$P_{j_2} = \sum j_2 / \sum ij$	—	—

Compiled by the authors.

where h is the step, value, at which the maximum (upper limit) of the previous interval has to be increased; $x_{\max}$ is the maximum value in the selection; and $x_{\min}$ is the minimum value in the selection.

Variation of the level of development of the components of the infrastructure is determined according to the following formula:

$$v = \frac{\sigma \times 100\%}{x_{\text{ave}}}, \quad (9.4)$$

where v is the variation (per cent deviation) of observations from direct average of the selection; σ is the direct average (standard) deviation of the selection; and x_{ave} is the average of the arithmetic selection.

For verifying hypothesis H_{02} we determine the signs of deficit of infrastructural provision in view of its components. Deficit is treated as the values of the indicators of development of infrastructure below 80 points (out of 100). For representativeness and simplification of treatment, direct averages of the values of the indicators in view of the infrastructure components are considered. If direct averages are below 80 points, the offered hypothesis H_{02} is considered proved.

The research objects are 16 countries that are characterized by the highest number per 10,000 workers in industry (according to Forbes Statista). The source of statistical data on the level of development of infrastructural provision (in view of its components) is materials from the Global Competitiveness Report 2018, prepared by the specialists of the World Economic Forum. Within this report, the Global Competitiveness Index 4.0 2018 is calculated, which reflects the level of development of the following components of infrastructural provision of Industry 4.0:

- Institutional infrastructure (Institutions);
- Transport infrastructure (Infrastructure);
- Information and communication infrastructure (ICT adoption);
- Market infrastructure (Macroeconomic stability);
- Infrastructure of healthcare (Health);
- Educational infrastructure (Skills);
- Product infrastructure (Product market);
- Personnel infrastructure (Labor market).

The initial basis for statistical data for this research is given in [Tables 9.2 and 9.3](#).

This research shows that it is necessary to use the economic and mathematical methodology for studying Industry 4.0. Qualitative analysis, which is successfully used during socioeconomic research, does not allow for precise measuring of the level of development of Industry 4.0 or its contribution into the economy's development. That is why it is suggested to use mathematics when studying Industry 4.0 to obtain the most objective and correct results and compiling correct conclusions and effective scientific and practical recommendations.

Table 9.2 Number of robots per 10,000 workers in industry in the top 16 countries.

Country	Number of robots per 10,000 workers in industry, units
South Korea	631
Singapore	488
Germany	309
Japan	303
Denmark	211
United States	189
Italy	185
Spain	160
Canada	145
France	132
Switzerland	128
Australia	83
United Kingdom	71
China	68
India	3
Russia	1

Compiled by the authors based on Forbes Statista (2019).

9.4 Results

9.4.1 The essence and specific features of the Fourth Industrial Revolution and advantages of automatized production on the basis of the Internet of Things

The essence of the Fourth Industrial Revolution (transition to Industry 4.0) consists in the change of the technological mode, due to which technical (in this case, digital) devices pass from the sphere of labor means to the sphere of objects (subjects) of labor. Its specific features, as compared to previous industrial revolutions, are reflected in [Table 9.4](#).

As can be seen from [Table 9.4](#), during all previous (1st, 2nd, and 3rd) industrial revolutions, automatization was incomplete, that is, mandatory participation of humans in production and distributive processes of economic activities remained. The Fourth Industrial Revolution enabled complete automatization—human participation in production and distributive processes of economic activities becomes optional; humans are either removed from these processes or go to the background.

Subjects of production during all previous industrial revolutions were stable/unchanged and included personnel and managers of companies. That is why the social consequences of the revolutions led to the necessity for retraining and

Table 9.3 Level of development of the components of infrastructural provision of Industry 4.0 in the selected countries, points 1–100 (the higher the better).

Country	1. Institutions	2. Infrastructure	3. ICT adoption	4. Macroeconomic stability	5. Health	6. Skills	7. Product market	8. Labor market
South Korea	65.4	91.3	91.3	100.0	96.1	73.6	56.2	62.4
Singapore	80.7	95.7	85.2	92.6	100.0	76.0	81.2	80.2
Germany	73.5	90.2	69.3	100.0	94.5	85.4	72.0	74.1
Japan	71.1	91.5	87.4	93.9	100.0	73.7	72.9	71.1
Denmark	75.9	86.3	82.3	100.0	93.4	84.9	66.9	78.0
United States	74.6	89.5	71.2	99.6	86.5	86.3	73.8	81.9
Italy	56.4	83.1	60.3	85.0	99.2	70.1	62.6	58.1
Spain	64.5	89.1	73.8	90.0	100.0	70.7	62.0	59.5
Canada	75.5	80.6	68.6	100.0	97.5	81.0	64.9	77.0
France	69.5	90.1	71.1	99.9	99.0	72.6	62.5	61.5
Switzerland	77.1	93.3	77.0	99.4	99.8	87.3	66.8	80.4
Australia	73.6	77.9	73.5	100.0	98.5	81.0	70.2	68.5
United Kingdom	76.8	89.0	71.1	100.0	93.9	80.2	68.7	76.5
China	54.6	78.1	71.5	98.3	87.0	64.1	57.4	59.3
India	57.9	66.8	61.1	89.7	59.0	54.5	50.9	58.3
Russia	52.7	72.2	72.1	87.5	68.5	68.5	54.2	59.5

Compiled by the authors based on [World Economic Forum \(2019\)](#).

Table 9.4 Specific features of the Fourth Industrial Revolution (transition to Industry 4.0), as compared to previous industrial revolutions.

Criterion of comparison	All previous (1,2,3) industrial revolutions	The Fourth Industrial Revolution
Automatization	Incomplete (human participation is optional)	Full (human participation is optional)
Subjects of production	Stable/unchanged (only personnel and managers)	New economic subjects appear: intellectual digital devices (e.g., robots)
Type of communications (subject–object)	Mainly: • “human–human” (intersubject communications and personnel management) • “human–machine” (programming of devices, e.g., conveyor)	Additionally: • “machine–human” (intellectual decision support) • “machine–machine” (management of digital devices by AI with the help of the Internet of Things)

Developed and compiled by the authors.

advanced training of personnel. In the course of the Fourth Industrial Revolution, new economic subjects appear: intellectual digital devices (e.g., robots). Replacing humans (ousting them from production and distributive processes of the economic activities), they cause new social consequences, connected to growth of unemployment and mastering of subject and subjective communications between people and digital devices.

This brings us to the third specific feature of the Fourth Industrial Revolution. In the first three industrial revolutions, two types of communications were mainly available:

- “Human–human”: intersubject communications (e.g., two or more employees and two or more managers) and management of personnel;
- “Human–machine”: programming of devices (e.g., conveyors).

During the Fourth Industrial Revolution in the conditions of Industry 4.0, there appear (apart from the existing two) new types of communications:

- “Machine–human”: intellectual decision support;
- “Machine–machine”: management of digital devices by AI with the help of the Internet of Things.

The determined specific features of the Fourth Industrial Revolution predetermine the advantages of automatized production on the basis of the Internet of Things under machine control (AI) as compared to modern mechanized production under human control (Table 9.5).

As can be seen from Table 9.5, one of the advantages is optimization of the production regime. Modern mechanized production under human control is conducted in daytime with standard quality and cost; and in nighttime with reduced quality and/or higher cost. Automatized production on the basis of the Internet of Things under machine control (AI) is conducted 24/7 with standard (unchanged) quality and cost, which ensures growth of production capacity and increase of the production scale.

Another advantage is a reduction of entrepreneurial risks. During the modern mechanized production under human control, entrepreneurial risks are high due to incomplete consideration of factors and imperfect policies. Automatized production on the basis of the Internet of Things under machine control (AI) allows reducing entrepreneurial risks due to a fuller consideration of factors and improved policy.

Another advantage is a reduction of products' cost. Modern mechanized production under human control leads to an increase of cost (incomplete realization of the potential of its reduction) due to excessive spending of resources.

Table 9.5 Advantages of automatized production on the basis of the Internet of Things under machine control (AI) as compared to modern mechanized production under human control.

Criterion of comparison	Modern mechanized production under human control	Automatized production on the basis of the Internet of Things under machine control (AI)
Regime production	During daytime with standard quality and cost; during nighttime with reduced quality and/or higher cost	24/7 with standard (unchanged) quality and cost: growth of production capacity and increase of production scale
Entrepreneurial risks	High due to incomplete consideration of factors and imperfect policy	Reduced due to full consideration of factors and improved analytics
Cost of products	Increased due to excessive spending of resources	Reduced due to saving of resources
Ecological effectiveness of production	Reduced due to incomplete control of waste and its large volume	Increased due to better control and minimization of production waste
Production safety	Necessity for placing production near large cities (metropolis), high risks of unhealthy work and trauma for employees	Possibility of placing production far from people; due to automatization, trauma and damage to health of employees could be excluded (prevented)
Level of hi-tech products	Reduced due to limited human capabilities and means of production mechanization	Increased due to automatization and usage of high-precision digital technologies

Developed and compiled by the authors.

Automatized production on the basis of the Internet of Things under machine control (AI) allows reducing the cost of industrial products due to saving of resources.

The advantages also include increased ecological effectiveness of production. Modern mechanized production under human control is characterized by reduced ecological effectiveness due to incomplete control over expenditures and their large volume. Automatized production on the basis of the Internet of Things under machine control (AI) has increased ecological effectiveness due to fuller control and minimization of production waste.

The advantages also include increased safety of production. Modern mechanized production under human control predetermines the necessity for placing production near large cities (metropolis) and high risks of unhealthy labor and trauma for employees. Automatized production on the basis of the Internet of Things under machine control (AI) allows placing production far from people, and automatization allows excluding (preventing) trauma and damage to health of employees.

The final distinguished advantage is an increase in the technological level of products, and therefore competitiveness and sustainability of growth and development of entrepreneurship and the economy as a whole. During modern mechanized production under human control, the hi-tech nature of products is low due to limited human capabilities and means of production mechanization. Automatized production on the basis of the Internet of Things under machine control (AI) allows increasing the hi-tech nature of products (manufacturing more complex products) due to automatization and usage of high-precision digital technologies.

9.4.2 Modeling of production and distribution processes in the Internet economy during automatized production on the basis of the Internet of Things

Based on the concept of the Internet economy, we performed modeling of production and distribution processes of automatized production on the basis of the Internet of Things (Fig. 9.1).

As shown in Fig. 9.1, in the model of production and distribution processes in the Internet economy during automatized production, the Internet of Things is a systemic element, which ensures integration and communication of all human and machine components (participants) of these processes. Though AI is a connecting link, it uses the Internet of Things during execution of all functions, which allows characterizing their importance in automatized production as equal.

In the compiled model, we see the machine block, which consists of AI (controlling component that makes decisions) and digital devices, for example, production robots (controlling component—performer), and the human block, which consists of a company's management, state, consumers, and other parties that are

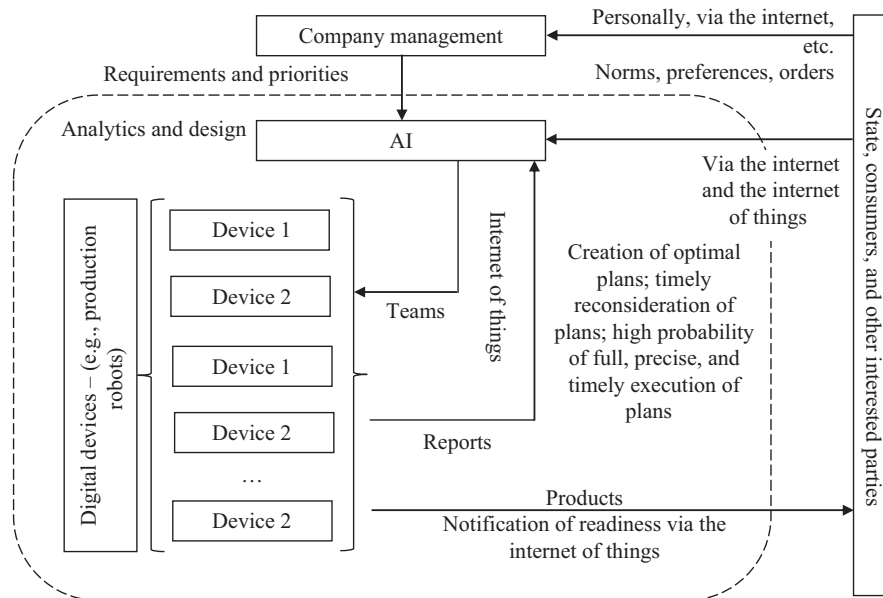


FIGURE 9.1 The model of production and distribution processes in the Internet economy during automatized production on the basis of the Internet of Things.

Developed and compiled by the authors.

interested in the company's activities (e.g., residents who live on the territory of the company's location but do not consume its products). Communication between these blocks is performed via interaction of humans and AI according to the communications type "human–machine."

Interested parties dictate their norms and pass their preferences and orders to the company's management (e.g., personally, via the Internet, via the phone, etc.) and to AI (via the Internet and the Internet of Things in a formalized form). The company's management sets the requirements and priorities for AI, which collects reports from all digital devices, conducts analytics, design, and planning of production and passes the orders to digital devices. Consumers are automatically notified on readiness of the products, and then the products are supplied (sold).

9.4.3 Infrastructural provision of automatized production on the basis of the Internet of Things: Specific features, deficit, and perspectives of overcoming the deficit

Based on the initial basis of statistical data from Table 9.2, we use the Sturges' rule (9.2) for determining the optimal number of intervals in which the selection of the number of robots per 10,000 workers in industry is to be divided; it consists

of 16 objects (countries, i.e., $N = 16$): $Q = 1 + 3322 \times \ln 16 = 5$. Formula (9.3) is used for determining the step by which the maximum (upper limit) of the previous interval is to be increased: $h = (631 - 1)/5 = 126$. Thus, we have the five following intervals:

- 1–127: from $x_{\min}$ to $(x_{\min} + h)$;
- 128–253: from $(x_{\min} + h + 1)$ to $(x_{\min} + h + 1 + h)$;
- 254–379: from $(x_{\min} + h + 1 + h + 1)$ to $(x_{\min} + h + 1 + h + 1 + h)$;
- 380–505: from $(x_{\min} + h + 1 + h + 1 + h + 1)$ to $(x_{\min} + h + 1 + h + 1 + h + 1 + h)$;
- 506–631: from $(x_{\min} + h + 1 + h + 1 + h + 1 + h + 1)$ to $(x_{\max})$.

The results of distribution of observations for the set criteria are shown in Table 9.6.

As can be seen from Table 9.6, in the first interval (1–127) there are five observations (31.25% of the selection's countries), in the second (128–253) seven observations (totally in two intervals—75% of countries), in the third interval two observations (totally in three intervals—87.50% of countries), in the fourth interval one observation (totally in four intervals—93.75% of countries), and in the fifth (last) interval one observation (totally in five intervals—100% of countries).

Based on the data in Table 9.3, we performed a calculation of variation (per cent deviation of the observations from direct average) of the level of development of the components of infrastructural provision of Industry 4.0 in the selected countries (Table 9.7, Fig. 9.2).

As can be seen from Table 9.7 and Fig. 9.2, the lowest variation in the level of development of the components of infrastructural provision of Industry 4.0 is observed in Singapore (9.95%), and the highest in South Korea (21.48%), Italy (21.67%), and China (21.79%). In Russia, variation constitutes 16.97%. The performed calculations allow compiling of the contingency table and using it for verifying hypothesis H_{01} with the help of Pearson's chi-squared test (χ^2) (Table 9.8).

As can be seen from Table 9.8, the probability of the selection's element being in the interval 128,000–253,000 robots per 10,000 employees in industry

Table 9.6 Interval distribution of the number of robots per 10,000 workers in industry in the top 16 countries.

Interval	Frequency (number of observations in interval)	Integral% (calculated by growing result)
1–127	5	31.25
128–253	7	75.00
254–379	2	87.50
380–505	1	93.75
506–631	1	100.00

Calculated and compiled by the authors.

Table 9.7 Calculation of variation of the level of development of the components of infrastructural provision of Industry 4.0 in the selected countries.

Country	Direct average (x_{ave}), points	Standard deviation (σ), points	Variation (v), %
South Korea	79.5	17.0847	21.48
Singapore	86.5	8.59767	9.95
Germany	82.4	11.6734	14.17
Japan	82.7	11.7742	14.24
Denmark	83.5	10.3168	12.36
United States	82.9	9.5361	11.50
Italy	71.9	15.5715	21.67
Spain	76.2	15.0082	19.70
Canada	80.6	12.4876	15.49
France	78.3	15.7114	20.07
Switzerland	85.1	11.8276	13.89
Australia	80.4	12.2933	15.29
United Kingdom	82.0	11.1537	13.60
China	71.3	15.5366	21.79
India	62.3	12.0089	19.28
Russia	66.9	11.3534	16.97

Calculated and compiled by the authors.

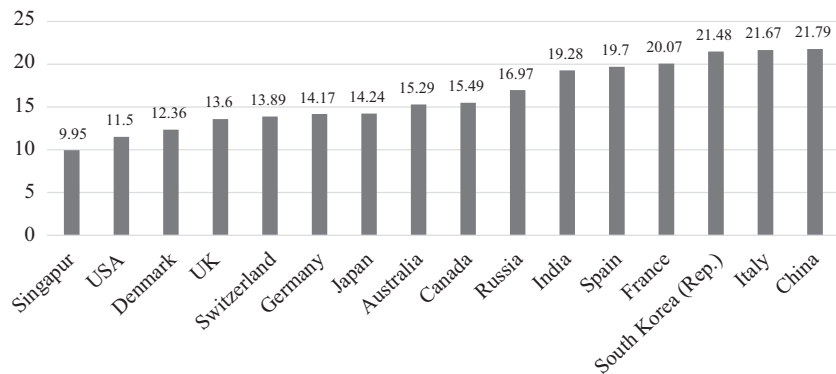


FIGURE 9.2 Coefficients of variation, %.

Developed and compiled by the authors.

($P_i = 0.44$) is the highest in the case of variation of the level of development of the infrastructure components above 15% ($P_j = 0.56$). Based on the data in Table 9.8 we perform a calculation of the observed value of with the help of Pearson's chi-squared test (χ^2) in the following way:

$\chi^2_{\text{obs}} = [(5-1)^2/1] + [(7-3)^2/3] + [(2-2)^2/2] + [(1-1)^2/1] + [(1-0)^2/0] = 16 + 5.33 + 0 + 0 + 0 + 21.33$. The table value $\chi^2_{\text{obs}} = 9.49$: calculated automatically at the significance level $\alpha = 0.95$, number of the degrees of freedom $f = (2-1) \times (5-1) = 4$. As $\chi^2_{\text{obs}} > \chi^2_{\text{table}}$ ($21.33 > 9.49$), the offered hypothesis H_{01} is proved.

Based on the statistical data from Table 9.3, we performed an analysis of sufficiency (and determining the deficit) of the infrastructural provision of industrial production on the basis of the Internet of Things (Fig. 9.3).

As is shown in Fig. 9.3, a direct average of the institutional infrastructure of industrial production on the basis of the Internet of Things (under the conditions of Industry 4.0) constitutes 68.7 points (below the set limit of 80 points). A direct average below the set limit of 80 points is also observed in the spheres of information and communication (74.2 points), educational (75.6 points), product (65.2 points), and personnel (69.1 points) infrastructure. A direct average above the set limit of 80 points is observed in the spheres of transport (85.3 points), market infrastructure (96 points), and healthcare infrastructure (92.1 points).

The level of development of infrastructure of industrial production on the basis of the Internet of Things (in the conditions of Industry 4.0) below the set limit of 80 points is observed in 93.8% (15 countries) in the sphere of institutional infrastructure; in 25% (four countries) in the sphere of transport infrastructure; in

Table 9.8 Contingency table, which is used for verifying hypothesis H_{01} with the help of Pearson's chi-squared test (χ^2).

Intervals of the number of robots per 10,000 workers in industry	Variation in the level of development of the infrastructure components, %		Sums for lines ($\sum i$)	Probability of the selection's element being in the studied interval (P_i), %
	Above 15%	Below 15%		
1–127	1	4	5	0.31
128–253	3	4	7	0.44
254–379	2	0	2	0.13
380–505	1	0	1	0.06
506–631	0	1	1	0.06
Sums for columns ($\sum j$)	7	9	16	—
Probability of the selection's element being characterized by the set variation (P_j), %	0.44	0.56	—	—

Calculated and compiled by the authors.

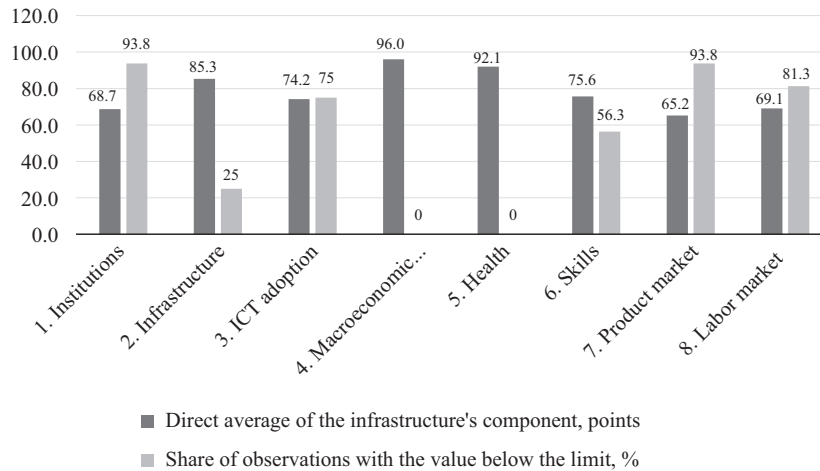


FIGURE 9.3 Data for analysis of sufficiency (and determining the deficit) of the infrastructural provision of industrial production on the basis of the Internet of Things.

Calculated and compiled by the authors.

75% (12 countries) in the sphere of information and communication infrastructure; in 56.3% (nine countries) in the sphere of educational infrastructure; in 93.8% (15 countries) in the sphere of product infrastructure; and in 81.3 (13 countries) in the sphere of personnel infrastructure. The performed calculations show a large deficit (insufficiency) of the infrastructural provision of industrial production on the basis of the Internet of Things (in the conditions of Industry 4.0) and confirm hypothesis H_{02} .

For overcoming the determined deficit of infrastructural provision of industrial production on the basis of the Internet of Things we developed the following perspective mechanism (Fig. 9.4).

As is shown in Fig. 9.4, during monitoring and regulation of the process of development of infrastructural provision of production on the basis of the Internet of Things the state has to take into account the systemic influence of infrastructure in view of the logic of its formation. At first (1), society sets demand for hi-tech products, and technological progress offers opportunities for the creation and development of technologies. This forms (2) a need for automatized production on the basis of the Internet of Things in Industry 4.0 in the development of technologies.

Changes in technological infrastructure lead to (3) a need for new personnel. The formation and development of personnel infrastructure require modernization of the educational infrastructure for satisfying (4) the need for new educational services (basic training, advanced training, etc.). A change of the educational infrastructure causes (5) the need for new social institutes, which, in its turn, forms new (6) needs in the sphere of transport infrastructure.

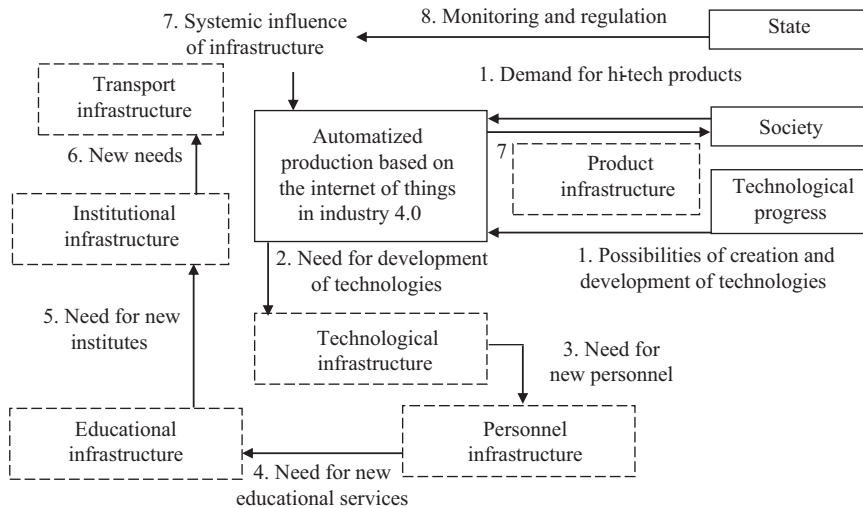


FIGURE 9.4 The mechanism of overcoming the deficit of and development of infrastructural provision of production on the basis of the Internet of Things.

Developed and compiled by the authors.

As a result (7), the systemic influence of the infrastructure on automatized production on the basis of the Internet of Things in Industry 4.0, which forms product infrastructure, is observed. The state conducts (8) monitoring and regulation of the whole infrastructure for the creation of a synergetic effect in the form of an increase of the effectiveness of entrepreneurship, economic growth, and the fullest satisfaction of society's needs for hi-tech products.

9.5 Conclusions

As a result of this research, it was determined that the Fourth Industrial Revolution (transition to Industry 4.0) has a range of specific features, as compared to previous industrial revolutions: completeness of automatization, emergence of new subjects of production (intellectual digital devices, e.g., robots), and creation of new types of communications: “machine–human” and “machine–machine.” Advantages of automatized production on the basis of the Internet of Things under machine control (AI) as compared to the modern mechanized production under human control are substantiated: more optimal regime of production, reduced entrepreneurial risks, reduced cost of products, higher ecological effectiveness of production, higher level of production safety, and higher level of hi-tech character (complexity) of products.

On the basis of the concept of the Internet economy, a model of production and distribution processes in the new type of industrial production is compiled. This model reflected the systemic role of the Internet of Things in automatized production of Industry 4.0. Significant influence of variation of the level of development (and therefore sufficiency in view of the determined deficit), which constitute infrastructure, on activity of automatization of production in Industry 4.0 on the basis of the Internet of Things (shown by the example of the number of robots in industry) is substantiated.

Differences in infrastructural provision of the distinguished types of industrial production are determined. The essence of the differences is that the market infrastructure and healthcare infrastructure are sufficient in all countries, while there is a deficit of institutional, transport, information and communication, educational, product, and personnel infrastructure. For overcoming this deficit, a mechanism of state monitoring and regulation of development of infrastructural provision of production on the basis of the Internet of Things is developed. This reflects the logic of formation of the needs for new infrastructure and their satisfaction by the state.

Thus, the organization of production on the basis of the Internet of Things is a perspective direction of modernization of modern entrepreneurship, as it allows increasing its effectiveness and competitiveness. A restraining factor on the path of implementation of this direction is a deficit of infrastructural provision of Industry 4.0, which is observed in all components of the infrastructure in most of the robotized countries of the world. Regulation of the infrastructure of Industry 4.0 is a complex task, which cannot be solved by the state independently—it is necessary to use monitoring of the market situation.

The need for new or improved infrastructural provision appears under the influence of growing demand for hi-tech products, due to growing possibilities of technological progress and the growth of innovative activity of entrepreneurship. That is why state stimulation of automatization of production on the basis of the Internet of Things in Industry 4.0 should envisage simultaneous implementation of measures in two directions.

First direction: creation of a favorable business climate for innovative development of entrepreneurship through stimulation of demand for hi-tech products, acceleration of technological progress (stimulation of development of science), and support for innovations-active entrepreneurship.

Second direction: satisfaction of the current needs of entrepreneurship in Industry 4.0 for infrastructure. The current “copying” of infrastructure (it is developed similarly to other countries) and planning (determining the needs for infrastructure, based on strategic priorities of economic growth) is inadmissible, as it might cause a mistake of the first degree (excessive spending of the assets of the state budgets due to the development of unpopular and unused infrastructure) and a mistake of the second degree (preservation of the deficits of popular infrastructure due to its uncertainty). The essence of state regulation of entrepreneurship of Industry 4.0 consists in the reduction of uncertainty and support for high flexibility of infrastructure.

Acknowledgment

This research was performed with financial support from the Russian Fund for Fundamental Research within scientific project No. 18-010-00103 A.

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Artificial intelligence as the core of production of the future: Machine learning and intellectual decision supports

10

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10.1 Introduction

Industry 4.0 is not another industrial revolution, but an unprecedented breakthrough in science and technology, which opens opportunities for a completely

new form of organization of production. During the first three industrial revolutions, modernization influenced only the manageable components of industrial entrepreneurship—technologies of production and certain technologies of distribution (e.g., means of shipment of goods). This common feature allows for conventional unification of the industrial revolution into a common stage of initial industrialization of the economy.

The Fourth Industrial Revolution is very different, as one of its main peculiarities is that it is the first time that technological progress has allowed modernizing of the technologies of management. In this context, technology is treated in a wide sense. The evolution of the concepts of management (e.g., the transition from norming of work to motivation and stimulation of work, and then to personnel marketing, or from monopolization of markets to pricing competition and then to competition on the basis of innovations) during the last two centuries took place with unchanged traditional technology of management, in which the subject was the hired manager in most cases.

In the production of the future in the conditions of Industry 4.0, a new technology of management will be accessible, in which artificial intelligence (AI) will be the subject. This will allow for the solving of a whole complex of the current problems of modern management. First, high and stable speed of decision-making with observation of all requirements will be achieved. Dynamics of the market environment require a quick reaction from the company. However, the processes of collection of data on the market situation, their analysis, and decision-making often require so much time that the managerial decision loses its actuality.

This problem is caused by the complexity of the bureaucratic machine of most modern corporate companies, due to which authorities of various managers could cross, their responsibility is limited and not controlled by the company's managers, and by limits of labor efficiency in the current technological mode. AI exceeds the modern managers as to the level of labor efficiency and can collect data very quickly, analyze them, and make decisions in real time (at the moment of query for decisions).

Second, it will be possible to solve complex managerial tasks. Most managerial tasks envisage consideration of many factors of the internal and external environment of the company and a lot of criteria of decision-making. Modern managers either simplify the tasks (taking into account only the most significant factors or the key criteria of decision-making) for their objective solution, or solve them intuitively (subjectively). As a result, nonoptimal (irrational) decisions are made, which reduce the effectiveness of the company's activities and increase the investment risk. AI can take into account many factors and criteria, and the completeness of analytics guarantees optimal (rational) decisions.

Third, the absence of contradiction of the interests of the company's owners and management will be ensured. Modern managers might seek their own interests in the process of company management (they are subjective)—for example, hiring and promoting not the best employees but the employees with whom they have informal (“shadow”) relations or concluding contracts not with the most profitable potential business partners (also due to informal interrelations).

Interests of owners and managers might differ. AI is always objective and acts in the company's interests, guaranteeing the most complete realization of the potential increase of its effectiveness.

The above advantages of the technology of automatized management make AI the core of future production. At the same time, a barrier to the path of modernization of the technology of company management is underdevelopment of the concept of future production, and, in particular, uncertainty of specific functions which AI will perform, as well as technical support for these functions. This chapter specifies the concept of production of the future by determining the perspective functions that AI might have and developing recommendations in the sphere of machine learning, which is technical support for these functions. The tasks of the chapter are as follows:

- Overview of the latest economic practice in the sphere of development of AI;
- Determining the scenarios of digital modernization of the modern economy depending on the functions of AI in the organization and management of production and distribution processes in the future;
- Development of the algorithms of AI learning for execution of various functions within the compiled scenarios.

10.2 Literature review

The concept of production of the future is developing within the theory of Industry 4.0 and has an important role in it—which led to a large number of works devoted to the development of this concept. Researchers analyze the essence and principles of the work of AI and consider the perspectives and offer practical solutions in the sphere of application of AI in solving the topical tasks of Industry 4.0. Thus, [Duan et al. \(2019\)](#) believe that, in the age of Big Data, AI is an inseparable component of the process of decision-making, though its role in this process could be different.

[Allam and Dhunny \(2019\)](#) name three breakthrough technologies of the modern time: Big Data, AI, and “smart” technologies (studied by the example of “smart” cities) and substantiate that these technologies are a system. [Wirtz and Müller \(2019\)](#) highlight the possibility to integrate AI into the system of e-governance, noting that this will allow enhancing of the effectiveness of management. [Popkova and Sergi \(2019\)](#) and [Popkova et al. \(2019\)](#) note wide perspectives of application of AI in the modern Russian practice of state management of the economy under the condition of its joint usage with the Internet of Things (systemic modernization).

[Bottani et al. \(2019\)](#) discuss the use of AI in the wholesale area. [Jakšič and Marinč \(2019\)](#) study the interconnection between bank activities and IT and come to the conclusion that AI plays a very important role in FinTech. Developing the previous ideas, [Belanche et al. \(2019\)](#) write that AI in FinTech could be used for managing robot-consultants for improving customer service. [Muñoz-Izquierdo](#)

et al. (2019) believe that AI could be useful during external auditing to forecast companies' bankruptcy risk.

Chopra (2019) notes the increased complexity of motivation of Indian buyers for using AI due to mistrust of it and security problems. Tubaro and Casilli (2019) discuss the use of AI in car building, and Petrenko et al. (2018) in retail and provision of services in the postindustrial economy in the interests of its sustainable development. MacAk et al. (2017) note wide perspectives of application of AI in marketing for modeling and managing consumer behavior. Petrenko and Shevyakova (2019) note high interest in AI in the modern economic systems—in particular, they note that AI is considered as a breakthrough technology in the digital economy of Kazakhstan.

Other authors focus on the development of AI—either on the technical component of this issue (e.g., development of computer software) or the philosophical (e.g., reflection on cognitive capabilities of computer and critical analysis of machine decision-making). The methodological basis is the concept of a “knowledge economy,” in which knowledge is considered as a product (result) of intellectual activities, where the subject is human or AI.

Shank et al. (2019a,b) write that emotions play an important role in the process of human perception and treatment of a situation. The absence of emotions with AI, on the one hand, allows it to think rationally, and, on the other hand, hinders it from perceiving the context of decision-making and may distort them, reducing the effectiveness of economy management. Townsend and Hunt (2019) state that entrepreneurial activities become a more creative process in the age of AI, as entrepreneurs have to show high flexibility during programming of AI to ensure correct execution of the functions.

Torres (2019) notes that AI has many risks and new opportunities; thus, it should be implemented into economic practice gradually and with special care. Rolan et al. (2019) offer an opinion that AI has more humanity than humans—though this opinion is contradicted by many scholars. For example, Shank et al. (2019) note that AI could perform illegal offenses—thus, it is necessary to integrate it into the legal system of modern countries.

Benotsmane et al. (2019) consider the economic and social consequences and exploitation of intellectual industrial companies in Industry 4.0 and conclude that the central element is AI, which interact and controls industrial robots. Ilie et al. (2019) write about the wide perspectives of the applied usage of AI. Selvi Rajendran et al. (2019) note that AI, as well as human intellect, requires constant development. The scholars suggest to use the technologies of alternate realities in the process of AI learning.

Chrisinger (2019) states that solving many AI problems consists in education (machine learning), as it will allow—in the long-term—reducing or overcoming the gap between human and AI skills. Upadhyay and Khandelwal (2019) also confirm the necessity for AI learning to support its topicality (preventing its moral aging). Kanuck (2019) believes that humor, ethics, and honor determine human life in the age of AI.

Oravec (2019) emphasizes that while developing and implementing AI it is necessary to pay attention to ethical issues. In particular, it is suggested to use AI

not only in entrepreneurship but also in social provision for its automatization as a perspective direction of corporate social responsibility. [Donon \(2019\)](#) considers the practices of the knowledge economy in the world of IT to be a top priority. [Al-Filali and Gallarotti \(2012\)](#) state that the modern economic systems (shown by the example of Saudi Arabia) require intellectual development, in which AI has an important role.

[Popkova \(2019\)](#) confirms the existence of preconditions for the formation and development of Industry 4.0 in the conditions of a knowledge economy. [Ojanperä et al. \(2019\)](#) develop the scientific and methodological provision of the evaluation and analysis of the digital knowledge economy. [Holford \(2019\)](#) offers a hypothesis that the future of human creative knowledge is connected to the development of the digital economy and AI. [Ipcioglu \(2015\)](#) performs a comparative analysis of the practice of knowledge management in developing countries during the 2008 crisis and the age of digital technologies (2014) and comes to the conclusion that AI allows for the increase and systematization of knowledge, increasing the effectiveness of creations and management.

[Georgieva and Zia \(2013\)](#) write about the necessity for formalization and verification of knowledge management in the digital economy and in digital companies with the help of AI. [Hay and Kapitzke \(2009\)](#) determine the “smart state” of the knowledge economy, in which creativity is restored through subjectivity—these authors deem it necessary to refuse development of AI in favor of the development of human creativity. [Popkova and Parakhina \(2019\)](#) note the opportunities and limitations of managing the global financial system on the basis of AI. [Garina et al. \(2018\)](#) compare approaches to the development of industrial production in the context of development of a complex product and offer an optimal approach that envisages usage of AI.

Thus, the performed overview of the existing research and publications within the concept of production of the future has shown that despite the sufficient elaboration of the technical and philosophical components of AI usage, the organizational component is poorly studied. There remains uncertainty as to the organization of the process of work and the development (machine learning) of AI. This established uncertainty hinders the practical implementation of ready technical solutions and adoption of a new philosophy of Industry 4.0 by the modern entrepreneurship. This chapter aims to become a connecting element between the current needs of entrepreneurship in AI and accumulated scientific knowledge in the sphere of its development and usage, a “bridge” that would reflect the organization of production of the future.

10.3 Materials and method

The methodology of this research is based on the application of scenario modeling and analysis. As AI is being developed, only technologies of intellectual

decision support are used in economic practice. In the system of data of international statistics, accounting and measuring of activity and usage of these technologies are performed with the help of the indicator (in this work it is a factor variable— x) “Use of Big Data and analytics,” as processing and analysis of Big Data are performed automatically based on previous replacements of AI. This indicator is calculated by IMD experts during the compilation of annual rating of countries as to the level of digital competitiveness of their economy.

To describe the quantitative characteristics of the scenarios of digital modernization of the modern economy depending on functions of AI in organizations and management of production and distribution processes in the future, we use the following indicators (resulting variables):

- Indicator of global competitiveness of the economy in the conditions of Industry 4.0: Global Competitiveness Index 4.0 (y_1);
- Indicator of labor efficiency in the economy: GDP per hour worked (y_2);
- Indicator of innovative development of the economy: Global Innovation Index (y_3).

Regression analysis is used to determine the mathematical dependencies of resulting variables on factor variables and to compile the models of paired linear regression of the type $y = a + b \times x$. Also, coefficients of determination (R^2) are calculated, which reflect the level of connection between variables—however their values are given only for completeness of statistical analysis, while they do not influence the process of compilation of scenarios, as the scenarios are to reflect the general perspectives of usage of AI, and we do not set the goal of achieving their high precision (which is impossible due to the essential novelty of AI and the weakness of the statistical base of its research).

The research is performed based on the most up-to-date statistical data (for 2018), and scenarios are compiled for the period of 2019–2030. When compiling the scenario “Other conditions being equal,” we determine the annual growth rate of the value of the factor variable in 2019, as compared to 2018. The value of the factor variable in the forecast years is determined by multiplying the basic value (in the previous year) by the determined growth rate. The values of the factor variable within other scenarios are determined by the expert method. For achieving higher authenticity of forecast scenarios, the values of the variables are presented in the form of a trust interval (from the minimum forecast value to the maximum forecast value)—in practice it is expected that the factual value of the variable will be within the limits of this interval.

After the values of the factor variable within each scenario are determined, they are put into the regression equations for determining the values of the resulting variables. Direct averages of the variables are used for calculations (Table 10.1). The research objects are the 17 countries that show the highest economic activity in the sphere of development of AI—according to the ratings of the experts of the [China Institute for Science and Technology Policy at Tsinghua University](#) (China AI Development Report, 2018).

Table 10.1 Statistics of Big Data and its benefits in 2017–2018 by country.

	Use of Big Data and analytics, position in global ranking (2017)	Use of Big Data and analytics, position in global ranking (2018)	Global Competitiveness Index 4.0, Score 0–100 (best) (2018)	GDP per hour worked, USD (2018)	Global Innovation Index, score 0–100 (best) (2018)
Country	value x in 2017	x	y_1	y_2	y_3
China	21	12	72.6	16.0	53.06
United States	6	3	85.6	64.2	59.81
United Kingdom	28	11	82.0	52.8	60.13
Australia	37	23	78.9	52.7	51.98
Germany	39	41	82.8	60.5	58.03
Canada	9	10	79.9	49.5	52.98
France	49	42	78.0	60.2	54.36
Italy	50	55	70.8	47.9	46.32
Spain	58	57	74.2	47.4	48.68
India	22	19	62.0	10.1	35.18
Japan	59	56	82.5	41.8	54.95
South Korea	56	31	78.8	34.3	56.63
Netherlands	20	17	82.4	62.7	63.32
Switzerland	25	24	82.6	59.2	68.40
Brazil	54	59	59.5	3.3	33.44
Taiwan (China)	7	13	79.3	14.8	53.06
Russia	46	58	65.6	24.1	37.90
Direct average	34.47	31.24	76.32	41.27	52.25

Compiled by the authors based on [IMD, 2019](https://www.imd.org/wcc/world-competitiveness-center-rankings/world-digital-competitiveness-rankings-2018). World digital competitiveness ranking 2018. Available from: <https://www.imd.org/wcc/world-competitiveness-center-rankings/world-digital-competitiveness-rankings-2018> (accessed 29.06.19.), [OECD, 2019](https://data.oecd.org/prdty/gdp-per-hour-worked.htm#indicator-chart). GDP per hour worked: 2018, total, USD. Available from: <https://data.oecd.org/prdty/gdp-per-hour-worked.htm#indicator-chart> (accessed: 29.06.19.), [WIPO, 2019](https://www.wipo.int/publications/en/details.jsp?id=4330). Global innovation index 2018. Available from: <https://www.wipo.int/publications/en/details.jsp?id=4330> (accessed 29.06.19), and [World Economic Forum, 2019](http://reports.weforum.org/global-competitiveness-report-2018/competitiveness-rankings/). The global competitiveness report 2018: Global Competitiveness Index 4.0. Available from: <http://reports.weforum.org/global-competitiveness-report-2018/competitiveness-rankings/> (accessed 29.06.19).

10.4 Results

10.4.1 The new economic practice in the sphere of the development of artificial intelligence

As a result of studying the new practice in the sphere of development of AI, we compiled the following global ratings in 2018 (Figs. 10.1–10.4).

According to Fig. 10.1, the highest publication activity of countries in the sphere of research into AI in 2018 was observed in China (2349 articles with a high citation rate) and the United States (2241 articles with a high citation rate).

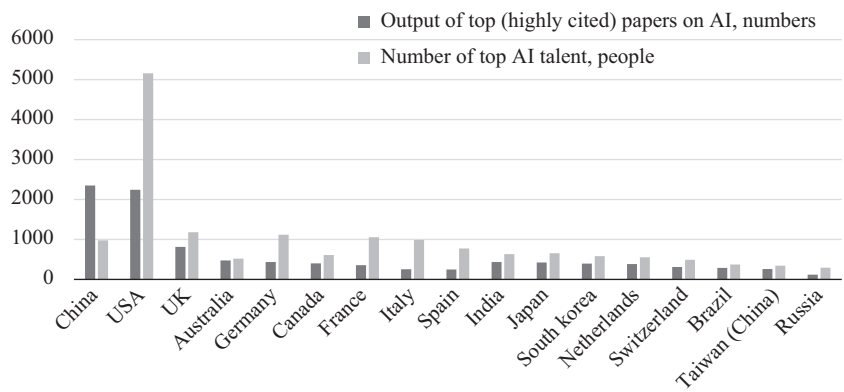


FIGURE 10.1 Publication activity of countries and talents in the sphere of research into artificial intelligence in 2018.

Compiled by the authors based on China Institute for Science and Technology Policy at Tsinghua University, 2019. China AI Development Report 2018. Available from: <http://www.sppm.tsinghua.edu.cn/eWebEditor/UploadFile/China_AI_development_report_2018.pdf> (accessed: 29.06.19.).

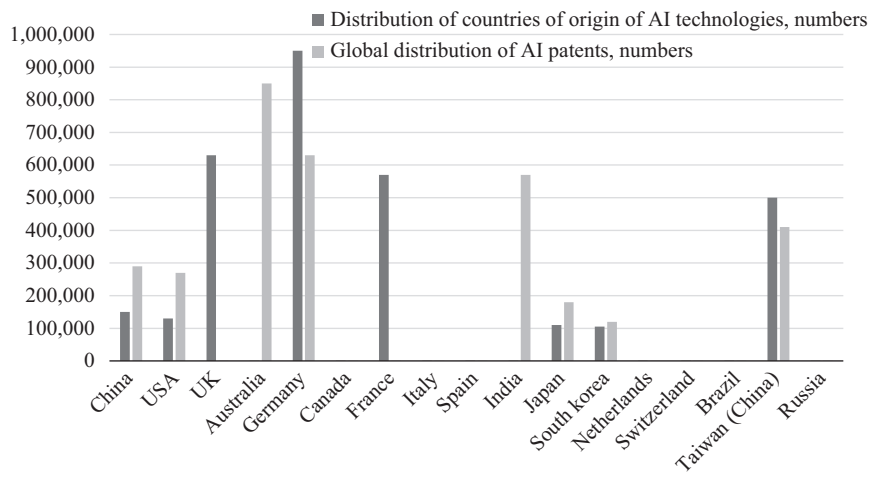


FIGURE 10.2 Distribution of technologies and patents by countries in the sphere of artificial intelligence in 2018.

Compiled by the authors based on China Institute for Science and Technology Policy at Tsinghua University, 2019. China AI Development Report 2018. Available from: <http://www.sppm.tsinghua.edu.cn/eWebEditor/UploadFile/China_AI_development_report_2018.pdf> (accessed: 29.06.19.).

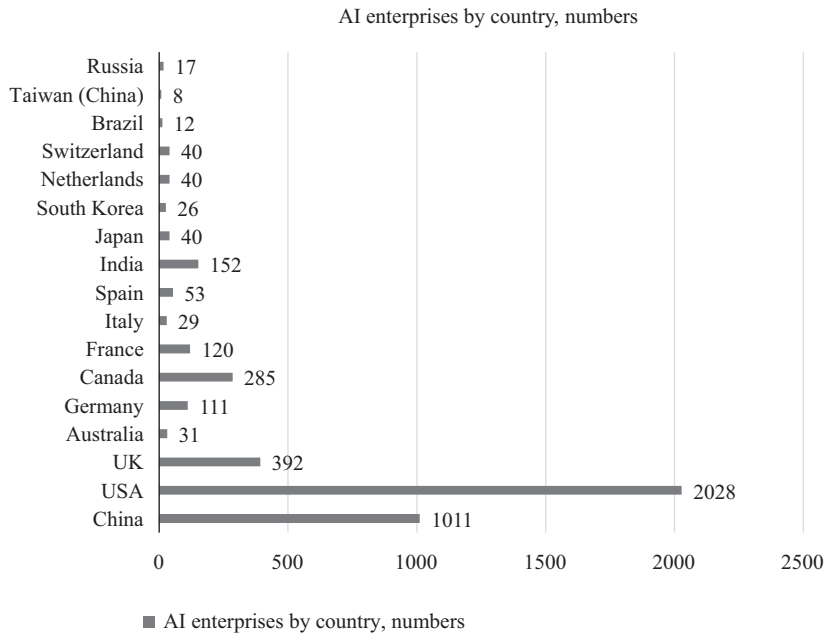


FIGURE 10.3 Number of companies that deal with development and implementation of AI in 2018.

Compiled by the authors based on China Institute for Science and Technology Policy at Tsinghua University, 2019. China AI Development Report 2018. Available from: <http://www.sppm.tsinghua.edu.cn/eWebEditor/UploadFile/China_AI_development_report_2018.pdf> (accessed: 29.06.19.).

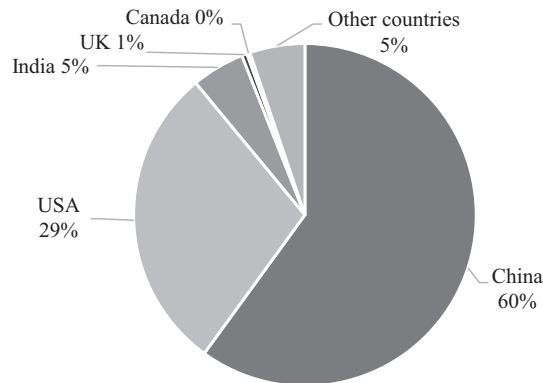


FIGURE 10.4 Distribution of global AI investment by country, percentage of total amount.

Compiled by the authors based on China Institute for Science and Technology Policy at Tsinghua University, 2019. China AI Development Report 2018. Available from: <http://www.sppm.tsinghua.edu.cn/eWebEditor/UploadFile/China_AI_development_report_2018.pdf> (accessed: 29.06.19.).

The lowest publication activity in the sphere of research into AI in 2018 among the studied top 17 countries was observed in Russia (115 articles with a high citation rate). The largest number of talent in the sphere of research into AI among the studied countries in 2018 was observed in the United Kingdom (1177 talents) and Germany (1119 talents). The lowest number of talents in the sphere of research into AI among the studied countries in 2018 was observed in Taiwan (China) (eight talents).

According to Fig. 10.2, the highest activity of countries on distribution of technologies in the sphere of AI in 2018 was observed in Germany (950,000 technologies) and the United Kingdom (630,000 technologies). The lowest activity of countries on distribution of technologies in the sphere of AI in 2018 was observed in Russia (260 technologies). The highest patent activity in the sphere of research into AI in 2018 was observed in Australia (850,000 patents) and Germany (630,000 patents). The lowest patent activity in the sphere of research into AI in 2018 was observed in Taiwan (China) (180 patents).

According to Fig. 10.3, the largest number of companies that deal with development and implementation of AI in 2018 was observed in the United States (2028), China (1011), the United Kingdom (285), India (152), and France (120). The lowest number of companies that deal with development and implementation of AI in 2018 was observed in Russia (17), Brazil (12), and Taiwan (China) (eight).

According to Fig. 10.4, in the global structure of investments into the development and implementation of AI, the leaders are China (60%) and the United States (29%). The shares of India (5%), the United Kingdom (0.5%), and Canada (0.3%) are also relatively high.

Thus, the performed overview of the new economic practice in the sphere of development of AI showed that not only developed countries (e.g., the United States and the United Kingdom), but also developing countries (e.g., China, Brazil, India, and Russia) are involved in this practice and occupy its leading positions. Therefore, AI is one of the most perspective digital technologies that could ensure leveling of disproportions in the development of modern economic systems.

10.4.2 Scenarios of digital modernization of the modern economy depending on the functions of artificial intelligence in the organization and management of production and distribution processes in the future

At present, AI is used only for intellectual support for decision-making. The scenario “Other conditions being equal” envisages preservation of AI’s current role in the organization and management of production and distribution processes in the future (until 2030) with moderate growth of its capabilities and an increase in its usage. The scenario “Partial automatization” envisages a large increase of

capabilities and ubiquitous and mass usage of AI—however, it will also preserve the role of intellectual support for decision-making.

The scenario “Full automatization” envisages a transition of production of the future to autonomous (not requiring human participation) machine management, in which AI makes decisions independently. The role of AI in the organization and management of production and distribution processes in the future (2030) within the scenario “Partial automatization” is shown in Fig. 10.5, and within the scenario “Full automatization” is shown in Fig. 10.6.

As is shown in Fig. 10.5, within the scenario “Partial automatization,” AI is a specific consultant of the manager. All digital data of the economic system (e.g., companies) are transferred to the digital storage of Big Data. These include data from external sources, “machine vision” (systems of photo and video surveillance

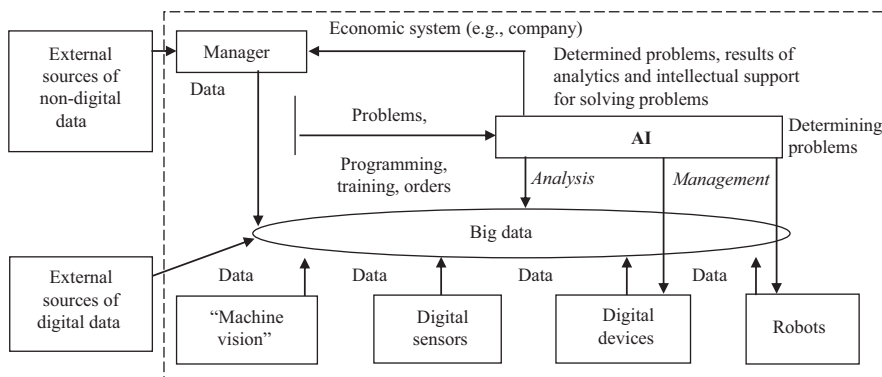


FIGURE 10.5 The role of artificial intelligence in the organization and management of production and distribution processes in the future (2030) within the scenario “Partial automatization.”

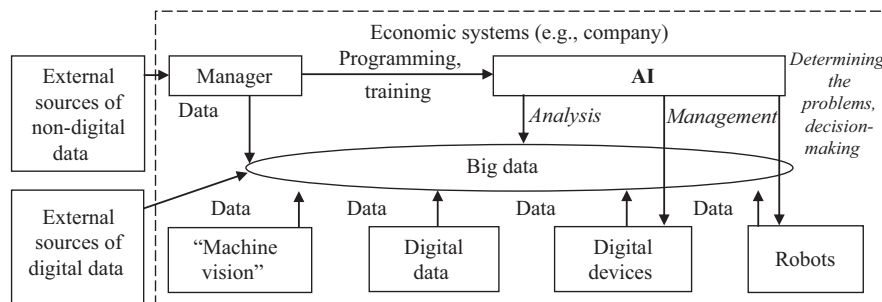


FIGURE 10.6 Role of artificial intelligence in the organization and management of production and distribution processes in the future (2030) within the scenario “Full automatization.”

at a company), digital sensors, digital devices, and robots. The manager receives nonformalized and nondigital data from external sources. The manager transforms these data into digital form and passes them to storage.

The manager determines the current problems of the economic systems and sends a query for their support from AI, which, in turn, also determines the problems and notifies the manager about them. AI performs analysis of Big Data, passes the results of analytics, and provides intellectual support for decision-making to the manager. It programs and teaches AI and issues orders. AI executes the manager's decisions, managing digital devices and robots of the company.

As is shown in Fig. 10.6, within the scenario "Full automatization," AI is a company's manager. It independently determines the problems and solves them. The hierarchy of management is eliminated—the manager and AI are at the same level (within the scenario "Partial automatization" the manager is at a higher level). The manager performs programming and training of AI (technical functions), but his managerial functions are reduced to the minimum.

Based on the data in Table 10.1, we built regression curves of dependencies of resulting variables on the factor variable (Fig. 10.7). The following equations of paired linear regression are obtained:

- $y_1 = -0.1757x + 81.811$. This equation means that a decrease in the use of Big Data and analytics by one position in the global rating leads to a growth of Global Competitiveness Index 4.0 by 0.1757 points. Coefficient of determination $R^2 = 0.2041$ shows a weak connection between the variables;
- $y_2 = -0.1611x + 46.298$. This equation means that a decrease in the use of Big Data and analytics by one position in the global rating leads to growth of GDP per hour worked by 0.1611 USD. Coefficient of determination $R^2 = 0.0253$ shows a weak connection between the variables;
- $y_3 = -0.2317x + 59.485$. This equation means that a decrease of the use of Big Data and analytics by one position in the global rating leads to a growth of Global Innovation Index 4.0 by 0.2317 points. Coefficient of determination $R^2 = 0.2330$ shows a weak connection between variables.

The growth rate of the use of Big Data and analytics in 2018, as compared to 2017, constituted 0.9041 (34.47/31.24). Due to this, the planned value of the factor variable in 2030 is calculated: 10th position. Within the scenario "Partial automatization," the value of the indicator use of Big Data and analytics will be in the interval from 6th to 9th position, and within the scenario "Full automatization" in the interval from 1st to 5th position. Quantitative characteristics of scenarios of digital modernization of the modern economy, depending on functions of AI in organization and management of production and distribution processes in the future (until 2030), are obtained by putting the set values of the factor variable in regression equations (separately) (Table 10.2).

Let us perform the calculations with which Table 10.2 was compiled. Within the scenario "Other conditions being equal" we put the forecast value (10th position) of the factor variable into the regression equation:

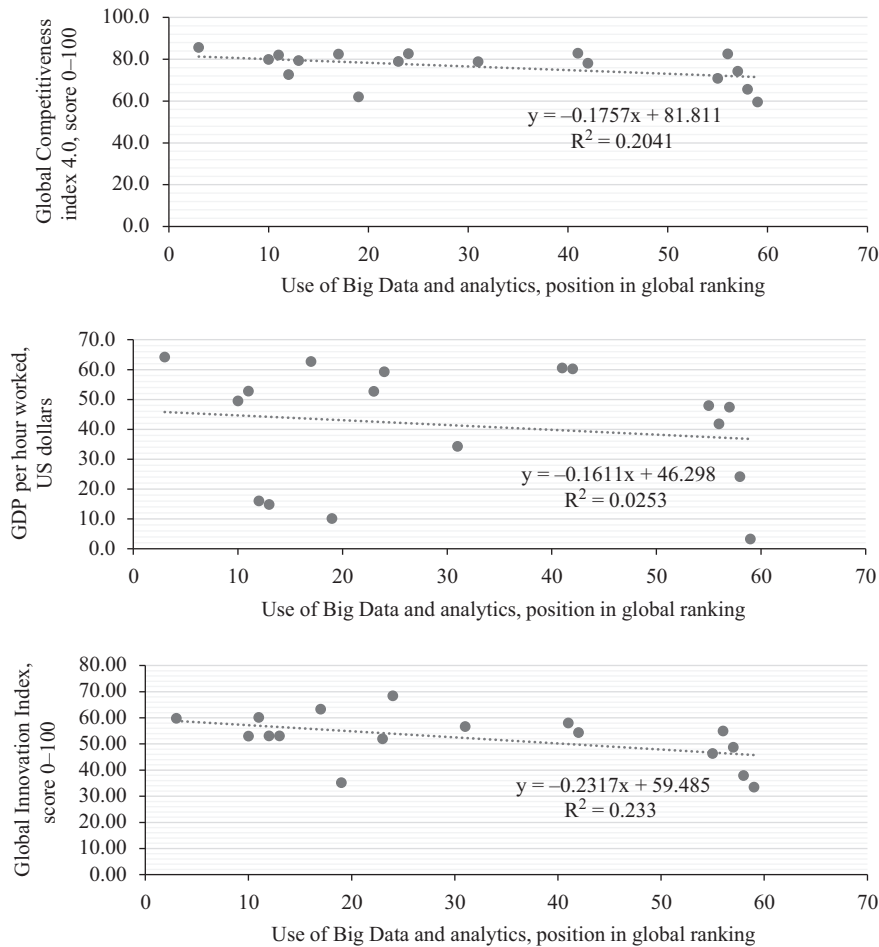


FIGURE 10.7 Regression curves of dependencies of the resulting variables on the factor variable.

$$\begin{aligned}
 -y_1 &= -0.1757 \times 10 + 81.811 = 80.05; \\
 -y_2 &= -0.1611 \times 10 + 46.298 = 44.69; \\
 -y_3 &= -0.2317 \times 10 + 59.485 = 57.17.
 \end{aligned}$$

The forecast values of the factor and resulting variables until 2030 within the compiled scenarios are shown in Figs. 10.8–10.11.

According to Fig. 10.8, the position of the use of big data and analytics will be decreasing annually, and will be minimal (maximum activity of usage) within the scenario “Full automatization.”

According to Fig. 10.9, the Global Competitiveness Index 4.0 will be growing annually until 2030. Within the scenario “Other conditions being equal” it

Table 10.2 Quantitative characteristics of scenarios of digital modernization of the modern economy depending on functions of artificial intelligence in the organization and management of production and distribution processes in the future (until 2030).

Variable	Scenario “Other conditions being equal”	Scenario “Partial automatization”	Scenario “Full automatization”
X_{min}	10	6	1
X_{max}	—	9	5
y_{1min}	80.05	80.76	81.64
y_{1max}	—	80.23	80.93
y_{2min}	44.69	45.66	46.14
y_{2max}	—	44.85	45.49
y_{3min}	57.17	58.09	59.25
y_{3max}	—	57.4	58.33

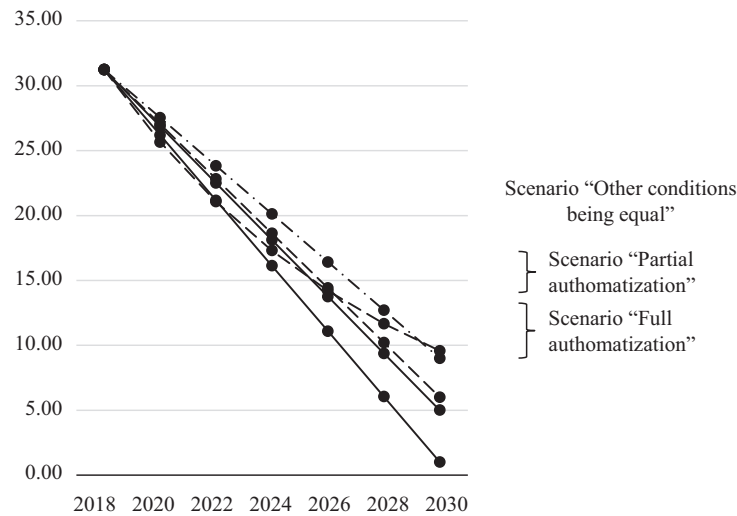


FIGURE 10.8 Forecast values of the use of Big Data and analytics (factor variable) until 2030 within the compiled scenarios, position in the global ranking.

constitutes 80.05 points, within the scenario “Partial automatization” from 80.23 points to 80.76 points, and within the scenario “Full automatization” from 80.93 points to 81.64 points.

According to [Fig. 10.9](#), GDP per hour worked until 2030 grows annually. Within the scenario “Other conditions being equal” it constitutes USD 44.69,

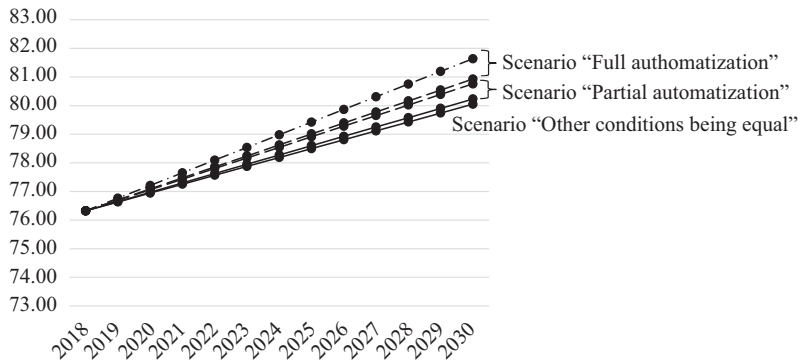


FIGURE 10.9 Forecast values of Global Competitiveness Index 4.0 (resulting variable) until 2030 within the compiled scenarios, score 0–100 (best).

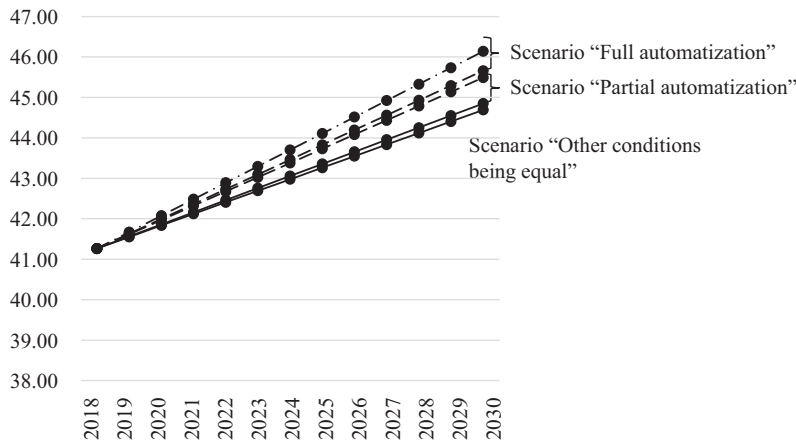


FIGURE 10.10 Forecast values of GDP per hour worked (resulting variable) until 2030 within the compiled scenarios, USD.

within the scenario “Partial automatization” it is USD 44.85–45.66, and within the scenario “Full automatization” it is USD 45.49–46.14.

According to [Fig. 10.9](#), the Global Innovation Index 4.0 until 2030 increases annually. Within the scenario “Other conditions being equal” it constitutes 57.17 points, within the scenario “Partial automatization” it is 57.40–58.09 points, and within the scenario “Full automatization” it is 58.33–59.25 points.

Thus, the highest (and best) value of all resulting variables is achieved within the scenario “Full automatization.” That is why this scenario is preferable (optimal). It should be also acknowledged that all studied scenarios are not necessarily

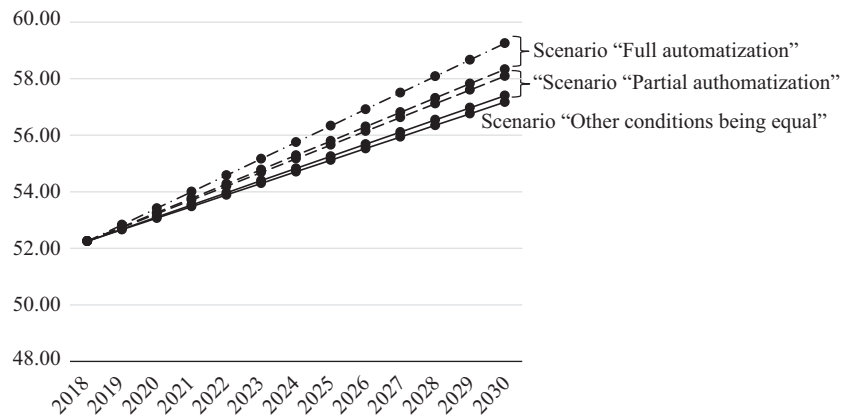


FIGURE 10.11 Forecast value of the Global Innovation Index (resulting variable) until 2030 within the compiled scenarios, score 0–100 (best).

alternative—they could be implemented simultaneously with differentiated approaches to application of AI in the economic systems (e.g., at different companies).

10.4.3 Algorithms of artificial intelligence training for the execution of various functions within the compiled scenarios

The context (e.g., the market environment) in which the economic system (e.g., company) functions, is subject to changes, and in the course of development of Industry 4.0 the needs of the economic systems for automatization of management grow. This causes the necessity for machine learning, aimed at improvement (increase of effectiveness, correction of errors) and expansion of capabilities of AI. Based on the concept of the “knowledge economy,” the necessity for machine learning is substantiated. We developed the algorithms of AI learning—separately for execution of the function of provision of intellectual decision support (Fig. 10.12) and execution of the function of independent decision-making (Fig. 10.13). The compiled algorithms reflect the logic (order) of implementation of managerial functions by AI.

As is shown in Fig. 10.12, the set of analyzed data, depending on the problem, is specified. Then, programming of new algorithms of analysis of Big Data and updating and uploading of new model problems depending on the combinations of the analyzed data and new model variants of solving the problems are performed. After that, the criteria of optimality of decision-making are specified, and variants of prioritization of optimality criteria are uploaded. Then, the forms of

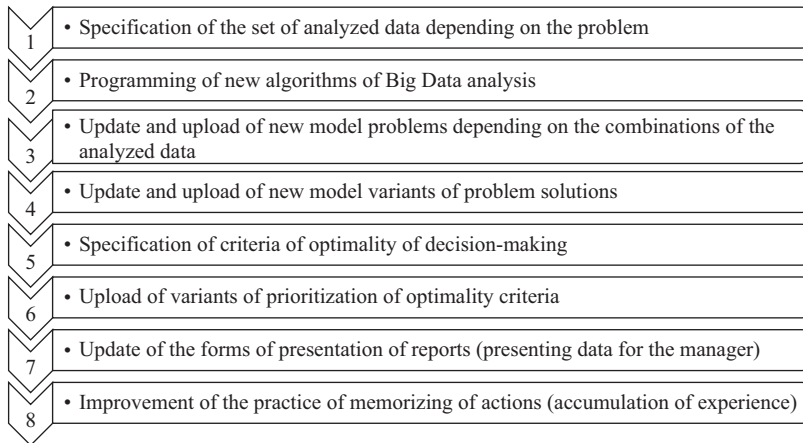


FIGURE 10.12 Algorithm of artificial intelligence learning for execution of the function of provision of intellectual support for decision-making.

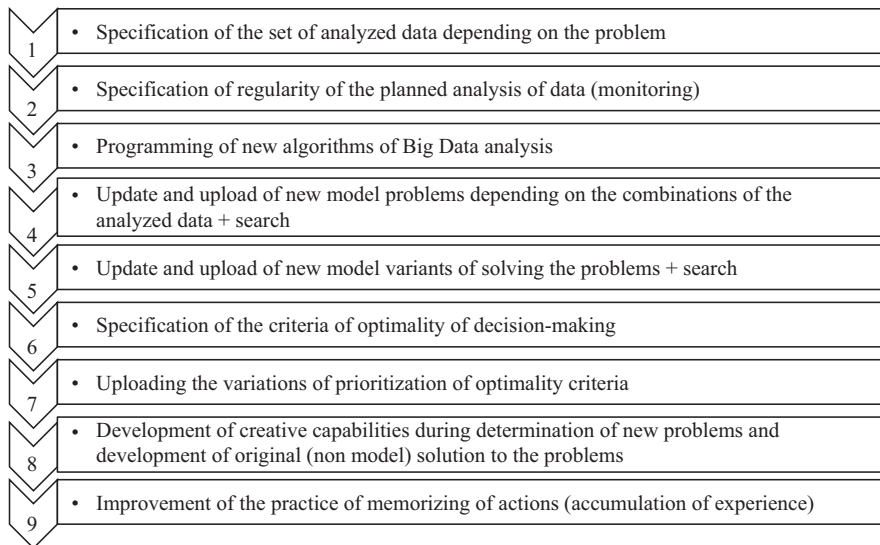


FIGURE 10.13 The algorithm of artificial intelligence training for execution of the function of independent decision-making.

presentation of reports (provision of data for the manager) are updated, and the practices of memorizing of actions (accumulation of experience) are improved.

As is shown in Fig. 10.13, the set of analyzed data is specified, depending on the problem. Then, regularity of the planned analysis of data (monitoring of

economic system) is specified. Programming of new algorithms of analysis of Big Data then is performed, and new model problems are uploaded depending on the combinations of the analyzed data; the order of search for additional problem in the Internet is provided. After that, criteria of optimality of decision-making are specified, and variants of prioritization of the optimality criteria are uploaded. Then, creative capabilities during development of new problems are developed, and original (nonmodel) solutions to the problems are prepared; also, the practice of memorizing actions (accumulation of experience) is improved.

From a mathematical point of view, the developed algorithms of AI training for executing the function of intellectual decision support and the function of independent decision support are described in the following way (mathematics is used at stages 1, 2, and 3):

1. Formation of arrays of data: $A, B, C, \dots, Z$;
2. Using and combining the methods of basic mathematics for data analysis:
 - Mathematical analysis. Example—calculating the derivative of composite functions A and B :

$$(A(B))' = A'(B) \times B'$$

- Linear algebra. Example—matrix analysis of the data array A :

$$A = \begin{pmatrix} a_{11} & a_{12} & a_{1n} \\ a_{21} & a_{22} & a_{2n} \\ a_{m1} & a_{m2} & a_{mn} \end{pmatrix}$$

- Methods of optimization. Example—system of equations of optimization of the values of data arrays A, B , and C :

$$\begin{cases} A > 0 \\ B < 0 \\ C \neq 0 \end{cases}$$

- Theory of probabilities and mathematical statistics. Example—classical calculation of probability (probability of the fact that the sum of the values of the first column of the matrix of data array A is above 0), α is the number of favorable results, and β is the number of results:

$$P(a_{11} + a_{21} + a_{m1} > 0) = \frac{\alpha}{\beta}$$

3. Criterion of optimality (example): $a_{11} + a_{21} + a_{m1} > 0$.

10.5 Conclusions

Thus, AI is the core of production of the future. However, its place and role (functions) in the organization and management of production and distribution processes in the future could be different. Within the scenario “Partial automatization,” AI

will continue providing analytical and consultation support for decision-making by the company's manager (human). Within the scenario "Full automatization," AI will oust the manager and take over his managerial functions (decision-making).

However, until 2030 AI will continue performing the programmed monitoring, analytical, and managerial algorithms with the help of the set technologies (formulas, logic). Thus, machine training will be required within both scenarios—the development and installation of computer software, algorithms, and technologies that improve the work of AI and expand its capabilities. Unlike most programs of mass usage, mass standardization of AI is complicated and even unacceptable, as instead of increasing competitiveness of the economic system it may lead to a reduction of their competitiveness.

That is why machine training will become a new function of the manager in the next 10 years. For successful execution of this function we offer the algorithms of AI learning. The developed algorithms fill the gap in the system of the existing scientific knowledge, which has uncertainty of practical applications of the existing technologies of AI development. The presented algorithms reflect the essence of organization of machine learning in a modern economic system.

The advantage of the performed research, as compared to other existing publications on the topic of AI, is that it is not limited by consideration of a separate component of development of AI (e.g., development of a new technology) but studies the process of organization of machine learning. Therefore the developed algorithms of AI learning form the scientific and methodological basis for practical implementation of AI into the activities of modern economic systems.

At the same time, it should be acknowledged that a certain limitation of the results of the performed research is the excessive focus on the managerial functions (monitoring and decision-making) of AI. Other functions, which will probably be possible in the future (e.g., communication and production), also require thorough research. Attention should be paid to the newly determined function of a manager in the future—AI training. The appearance of this function changes the set of manager competencies, and therefore the principles of his training and hiring. These issues should be studied in further research devoted to this topic.

Acknowledgment

This research was performed with financial support from the Russian Fund for Fundamental Research within scientific project No. 18-010-00103 A.

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Active digital manufacturing: Conceptual foundations and practical solutions

11

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11.1 Introduction

One of the key manifestations of the Fourth Industrial Revolution is the formation of the digital economy. It is formed under the influence of the two tendencies of recent years, which have transformed the social environment of the modern

economic systems. The first tendency: increase of the value of knowledge in society (popularization of higher education and life-long learning) and growth of demand for innovations (knowledge-intensive services and hi-tech goods). The second tendency: mass distribution of new information and communication (digital) technologies and their regular usage in social and economic processes by households.

The influence of these tendencies, together with globalization, has reduced the gap in the social environment of economic systems. As a result, in the countries that are inclined for conservatism (that have value traditions) and the countries that specialize in agriculture and services spheres, as well as countries that are based on an unskilled workforce, a digital society has been formed. Its specific features are the large number of digital devices and technologies with the population, high level of digital literacy, and high value of knowledge (in the forms of education and technologies) and innovations.

The digital society is a social environment that is favorable for the formation of a digital economy. The universal character of the social environment is the basis for a generalized treatment of the digital economy as an economic system in which digital technologies are used by the population during purchase and consumption of goods and services and conducting domestic households, by the state during regulation of economic activities and provision of state services, and by entrepreneurship in production and distribution processes.

However, two alternative approaches to the organization of digital manufacturing could be observed in practice—depending on the selected approach, the digital economy could remain within the third technological mode or move to the fourth technological mode (Industry 4.0). The first approach: passive digital manufacturing. This envisages fragmentary digital modernization of industrial production on the basis of widely accessible digital technologies—personal computers, mobile communications, the Internet, and technologies of intellectual support for model decision-making. In this case, production forms sociotechnical systems in which the key functions are performed by humans, and only certain routine operations are automatized—that is, the third technological mode is preserved.

The second approach: active digital manufacturing. This envisages full-scale digital modernization of industrial production on the basis of breakthrough digital technologies of Industry 4.0—cloud technologies, blockchain technologies, 3D printing, technologies of Big Data processing, the Internet of Things, AI, robotronics, manipulators, and unmanned transport vehicles. In this case, production forms cyberphysical systems in which the key functions are performed by machines with full or almost full automatization, and in which humans perform only the most creative operations—that is, transition to the fourth technological mode (Industry 4.0) takes place.

The differentiation of approaches to organization of digital manufacturing causes the scientific problem of determining the perspectives and substantiating the transition to Industry 4.0 (or refusal from it) at the level of macroeconomics

and microeconomics. This problem is narrowed down to determining which of the alternative approaches to organization of digital manufacturing is most preferable for the national economy and each company. This problem actualizes the development of the conceptual models, which allow for clear differentiation of passive and active digital manufacturing.

The purpose of this research is to develop scientific concepts that allow for clear differentiation and identification of passive and active digital manufacturing, to determine the current problems that hinder the formation and development of active digital manufacturing, and to offer recommendations for solving them. The set goal is achieved with the help of the following tasks:

1. Developing a scientific concept of active digital manufacturing; determining its principles, priorities, and differences from the concept of passive digital manufacturing (for formation of a comprehensive and clear theoretical basis of studying the research subject—active digital manufacturing);
2. Comparative analysis of advantages from the development of passive and active digital manufacturing (for substantiation of the advantages/preferences of digital manufacturing and expedience of transition to it from passive digital manufacturing);
3. Determining the current problems of starting and implementing active digital manufacturing and offering their perspective solutions.

11.2 Literature review

The theoretical basis of the scientific concept of active digital manufacturing includes works and publications, which we systematized and divided into three relative parts of economic knowledge. The first part: the digital economy as an economic system in which digital manufacturing takes place. This part is presented in [Pradhan et al. \(2019\)](#), in which the authors come to the conclusion that short-term and long-term dynamics of venture capital and economic growth is specific to the digital economy (shown by the example of European countries). The importance of building the digital economy in developing countries is emphasized in [Petrenko and Shevyakova \(2019\)](#) (using the example of the Republic of Kazakhstan).

[Islam and Eva \(2019\)](#) note that an important stage on the path to the digital economy is online trade. [Neeraj \(2019\)](#) focuses on the necessity of adopting special trade rules for the digital economy (using the example of the World Trade Organization). [Ansong and Boateng \(2019\)](#) note that the market environment in the age of the digital economy is most aggressive due to increased competition, which puts modern companies at the brink of collapse and creates the need for new business models for digital companies.

[Mueller and Grindal \(2019\)](#) discuss the flows of data in the digital economy; it is determined that information is a mobile factor of production, which plays the key

role in the activities of digital companies. [Watanabe et al. \(2018\)](#) note the high complexity of measuring GDP in the conditions of the digital economy. [Martin-Shields and Bodanac \(2018\)](#) substantiate that the digital economy stimulates overcoming the internal and external contradictions of economic systems (the term “peacekeeping” is offered to denote this effect); thus, the authors deem it necessary to stimulate the distribution of digital technologies for accelerating the growth and development of postcrisis economy and supporting its sustainability.

The second part: Industry 4.0 as the fourth technological mode, transition to which is performed as a result of development of active digital manufacturing. The work by [Horváth and Szabó \(2019\)](#) considers the driving forces and barriers of Industry 4.0 and substantiates that opportunities for transition to Industry 4.0 are different for multinational and small and medium-sized companies. [Huang et al. \(2019\)](#) also note the changes in the chain of creation of value in the conditions of Industry 4.0 (shown by the example of small and medium-sized companies). [Agostini and Filippini \(2019\)](#) determine organizational and managerial problems on the path to industry 4.0.

[Hamada \(2019\)](#) emphasizes the necessity for adapting management to the conditions of Industry 4.0 (shown by the example of decision-making). [Snudden \(2019\)](#) discusses the acceleration of technological progress in the conditions of the Fourth Industrial Revolution, connected to transition to Industry 4.0. [Castelo-Branco et al. \(2019\)](#) conduct an evaluation of the readiness of modern socioeconomic systems to Industry 4.0 and make the conclusion on the necessity for additional preparation (shown with the example of the EU countries).

Many researchers describe the perspective of the application of digital technologies to economic activities in the conditions of Industry 4.0: [Kunst et al. \(2019\)](#)—AI, and [Masood and Egger \(2019\)](#)—alternate reality. [Weber et al. \(2019\)](#) note the expedience of applying the technologies of Industry 4.0 in the activities of a state (shown by the example of the Austrian parliament). [Durana et al. \(2019\)](#) write about the formation of a culture of support for high-quality products by a production company as a path to adaptation of Industry 4.0. [Popkova \(2019\)](#) and [Popkova and Sergi \(2019\)](#) write about the preconditions for the formation and development of Industry 4.0 in the conditions of a knowledge economy and investment economy (using the example of Russia).

The third part: digital technologies that are used or that have the perspectives of usage in digital manufacturing (passive and active). This part is presented in the work by [Frank et al. \(2019\)](#), where the authors develop the models of implementing the technologies of Industry 4.0 into the activities of production companies. [Rawat et al. \(2017\)](#) present modeling of the growth of reliability of software of Industry 4.0. A whole range of scholars and researchers perform overviews of perspective digital technologies and possibilities of their practical application in the conditions of Industry 4.0.

[Goyal et al. \(2017\)](#) assess the efficiency of autonomous robots. [Nuccio and Guerzoni \(2019\)](#) consider the influence of the application of digital platforms on the market power in the data economy—the authors focus on technologies of

processing and analysis of Big Data. Roldán et al. (2019) offer a system of training for operators of Industry 4.0 at the assembly industrial companies, which is based on virtual reality. Benotsmane et al. (2019) analyze the economic and social consequences of the exploitation of intellectual factories in Industry 4.0 with an emphasis on modeling of the interaction between AI and robots.

Fahmfam and Hamidi (2019) studied the factors that influence the development and management of a “smart city” with use of a combination of Big Data, the Internet of Things, and technologies of cloud computations. Kyriakou and Loukis (2019) show that market strategy, specifics of organization of internal and external processes, flexibility, and susceptibility to innovations of personnel, as well as applied technologies, influence companies’ inclination for implementation of cloud computations. Engelenburg et al. (2019) develop the architecture of software that supports information exchange between companies for increasing public security and protection with the help of blockchain. Hart and Rao (2019) consider the perspectives of the development of 3D printing.

Zhao et al. (2019) discuss the necessity for regular updating of software for the devices that are responsible for supporting data confidentiality—for this, the authors recommend using blockchain and the Internet of Things. Ur Rehman et al. (2019) emphasize the key role of analytics of Big Data in the industrial Internet of Things. Osório and Pinto (2019) note wide opportunities and perspectives of development of the systems of autonomous transport vehicles under AI control.

Negash et al. (2017) suggest using technologies of a distributed register for detecting and preventing cyber-attacks in unmanned flying vehicles. Miller (2019) and Mazhar et al. (2019) study the specific features of communication between humans and AI. Yamamoto et al. (2019) point out the expedience of implementing manipulators at modern industrial companies. Popkova et al. (2019) offer a model of state management of the economy on the basis of the Internet of Things; and Popkova and Parakhina (2019) offer a model of management for the global financial system on the basis of AI.

Though these parts are peculiar to a high level of elaboration of their research objects (digital economy, Industry 4.0, and digital technologies that are used in production), the concept of active digital manufacturing has not been formed yet and requires specification (unification, reconsideration, and expansion of the existing knowledge) and clear differentiation (opposition) from the concept of passive digital manufacturing.

11.3 Materials and method

Despite the insufficient formation of these models and fragmentary character of scientific knowledge in the sphere of studying passive and active digital manufacturing (even these terms have not passed the scientific discussion), high interest in

Industry 4.0 as a source of potential multiple advantages (e.g., multiple increase of labor efficiency) leads to scholars and experts preferring active digital manufacturing. Contrary to this, we offer hypothesis H_0 —a favorable social environment (digital society) is insufficient for establishment and development of active digital manufacturing (unlike passive digital manufacturing)—transition to Industry 4.0 requires implementation of additional regulation measures from the state.

From an economic and mathematical point of view, the sense of the offered hypothesis H_0 exists in the absence of statistically significant advantages of active digital manufacturing as compared to passive digital manufacturing in countries with a favorable social environment for the development of the digital economy and, in particular, Industry 4.0. We verify this hypothesis with the help of the following sequence of actions:

1. Determining regression dependencies of the indicators that reflect the advantages of digital manufacturing (dependent variables), on the indicators that reflect the level of development of its certain type (independent variables): active or passive digital manufacturing. The indicators of advantages are a share of medium-tech and hi-tech production in the structure of added value in industry (calculated by the World Bank), share of hi-tech products in the structure of export (calculated by the World Bank), and the index of global competitiveness of the economy in the conditions of Industry 4.0 (calculated by the World Economic Forum).

The indicators of development of active digital manufacturing are the number of robots per 10,000 employees in industry (calculated by Forbes Statista) and indicators that are calculated by the European Commission within paragraph 4 Integration of digital technology of the report “Digital Economy and Society Index 2019”: 4a3 Big data and 4a4 Cloud. The indicators of development of passive digital manufacturing are indicators that are calculated by the European Commission within paragraph 4 Integration of digital technology of the report “Digital Economy and Society Index 2019”: 4a1 Electronic information sharing, 4a2 Social media, 4b1 SMEs selling online, 4b2 e-Commerce turnover, 4b3 Selling online cross-border.

2. Calculation of the sum of coefficients $b_1, b_2, \dots, b_n$ in the models of multiple linear regression of type $y = a + b_1 \times x_1 + b_2 \times x_2 + \dots + b_n \times x_n$ separately for active and passive digital manufacturing. Comparison of the received sums.
3. Determining the values of independent variables (separately for each type of digital manufacturing) for achieving the target values of dependent variables with the help of optimization modeling (simplex method). It is necessary to determine the differences between the extent of the increase of the scale of active digital manufacturing as compared to passive digital manufacturing for maximization of advantages. The target values of dependent variables are as follows (maximum value that could be achieved in practice): share of mid-tech and hi-tech production in the structure of added value in the industry

should constitute 85%, share of hi-tech products in the structure of exports should constitute 85%, and the index of global competitiveness of the economy in the conditions of Industry 4.0 should constitute 95 points.

4. Determining the growth of estimate values of independent variables as compared to their values in 2018 (in %) and calculation of direct average of growth for indicators of active and passive digital manufacturing separately. Comparison of the direct average of growth of indicators of the level of development of active and passive digital manufacturing.

If the sum of coefficients $b_1, b_2 \dots b_n$ for passive digital manufacturing equals or exceeds their sum for active digital manufacturing, and the growth of estimate values of independent variables with passive digital manufacturing is lower or equals the growth of values of independent variables with active digital manufacturing, hypothesis H_0 is considered to be proved; in the opposite case, it is considered to be disproved.

The objects for the research are European 10 countries for which index I-DESI (Digital Economy and Society Index) is calculated for 2018 and which show the highest values of the indicators of development of the digital society, according to the experts of the Dentsu Aegis Network (i.e., characterized by a favorable social environment for starting and developing digital manufacturing – passive and active) (Fig. 11.1).

As is seen from Fig. 11.1, the highest level of society's involvement in the processes of formation of the digital economy in 2018 among the countries of Europe is observed in Russia (50%), Spain (48%), and Italy (46%). The lowest

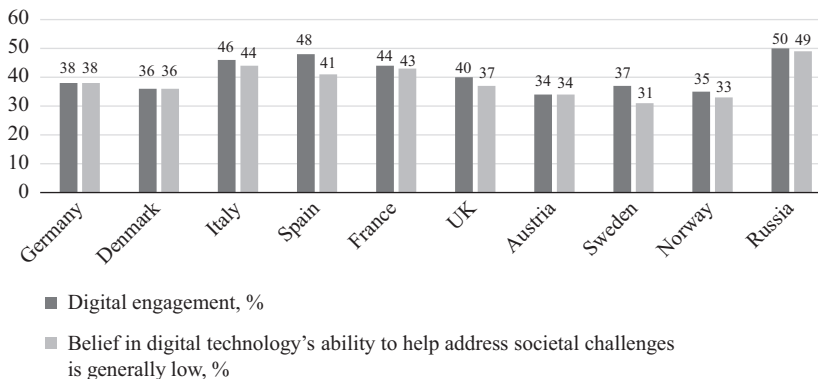


FIGURE 11.1 Indicators of the development of the digital society in countries of Europe, for which index I-DESI is calculated in 2018 (%).

Compiled by the authors based on *Dentsu Aegis Network, 2019. Digital Society Index 208*. Available from: https://d1iydh3qrygeij.cloudfront.net/Media/Default/landing-pages/Digital_society_index.pdf (accessed 01.07.19).

level of society's involvement in the processes of formation of the digital economy is shown by Austria (34%), Norway (33%), and Sweden (31%). The most pessimistic attitude toward digital technologies (belief in their poor capabilities in the stimulation of positive social changes) is also notable for Russia (49%) and Italy (44%). These data show contradictions in the digital society in European countries.

The initial data for the research are shown in [Tables 11.1](#) and [11.2](#). The data for Russia are given according to the materials of a short statistical collection "Digital economy 2019" of the Ministry of Digital Development and Mass Communications of the Russian Federation, the Federal State Statistics Service, and the National Research University "Higher School of Economics."

When determining the current problems of starting and implementing active digital manufacturing and their perspective solutions, we used the methods of SWOT analysis.

11.4 Results

11.4.1 The scientific concept of active digital manufacturing, its principles, priorities, and differences from the concept of passive digital manufacturing

Digital manufacturing is the pinnacle of industry's evolution. The idea of using digital technologies in industrial production predetermines the necessity for its foundation of a new, own, concept, which differs from the concept of predigital (mechanized) production. In [Fig. 11.2](#) we present the scientific concept of passive digital manufacturing, and in [Fig. 11.3](#), the concept of active digital manufacturing.

These concepts reflect the digital technologies that are used in industrial production and model organization of the production process, as well as show its subject and their hierarchical connections. The presented concepts reflect the maximum opportunities of automatization of industrial production with their technological mode, while in practice the activities of industrial companies might involve not all of the digital technologies that are shown in [Figs. 11.2](#) and [11.3](#).

As is shown in [Fig. 11.2](#), the scientific concept of passive digital manufacturing envisages that it is guided by a manager. It accepts orders and, in particular, Internet orders from consumers in any markets: B2B (business-to-business), B2G (business-to-government), and B2C (business-to-consumers). Marketing information from consumers (e.g., tendencies to change and the current consumer preferences) goes to the storage of digital data. Though a lot of data are in the electronic form, other forms are also used (e.g., paper carriers and nonformalized knowledge and information that the manager has).

The manager performs analytics of data and plans production with the help of intellectual support for decision-making. The compiled plans are moved to the design engineer, who designs the products and production. The approved projects

Table 11.1 Indicators of the development of active and passive digital manufacturing in society in the top 10 European countries as to the level of development of the digital society in 2018.

	Number of robots per 10,000 employees in industry	4a3 Big Data, % enterprises	4a4 Cloud, % enterprises	4a1 Electronic information sharing, % enterprises	4a2 Social media, % enterprises	4b1 SMEs selling online, % SMEs	4b2 e-Commerce turnover, % SME turnover	4b3 Selling online cross-border % SMEs
Country	x₁	x₂	x₃	x₄	x₅	x₆	x₇	x₈
Germany	309	15	12	38	16	19	9	11
Denmark	211	14	41	40	29	31	17	9
Italy	185	7	15	37	17	10	8	6
Spain	160	11	16	46	28	18	10	7
France	132	16	15	38	16	15	11	7
United Kingdom	71	15	30	19	42	19	11	9
Austria	0,05	6	11	40	21	13	7	14
Sweden	0,03	10	43	31	25	30	18	10
Norway	0,02	15	43	30	20	27	19	6
Russia	1	13	23	29	16	12	5	3

Compiled by the authors based on [European Commission, 2019. Digital Economy and Society Index 2019 – Country Reporting](https://ec.europa.eu/digital-single-market/en/news/digital-economy-and-society-index-desi-2019). Available from: <<https://ec.europa.eu/digital-single-market/en/news/digital-economy-and-society-index-desi-2019>> (accessed 01.07.19.), [Forbes Statista, 2019](https://www.forbes.com/sites/niallmccarthy/2018/04/25/the-countries-with-the-highest-density-of-robot-workers-infographic/#7c0538a01853). The countries with the highest density of industrial robots. Available from: <<https://www.forbes.com/sites/niallmccarthy/2018/04/25/the-countries-with-the-highest-density-of-robot-workers-infographic/#7c0538a01853>> (accessed 27.06.19.), [Ministry of Digital Development and Mass Communications of the Russian Federation, Federal State Statistics Service, National Research University "Higher School of Economics", 2019. The digital economy – 2019: a short statistical collection](https://www.hse.ru/data/2018/12/26/1143130930/ice2019kr.pdf). Available from: <<https://www.hse.ru/data/2018/12/26/1143130930/ice2019kr.pdf>> (accessed 01.07.19.).

Table 11.2 Indicators of advantages from the development of digital manufacturing in society in the top 10 European countries as to the level of development of digital society in 2018.

	Medium- and high-tech industry (including construction), % manufacturing value added	High-technology exports, % of manufactured exports	Global Competitiveness Index 4.0, score 0–100 (best)
Country	y_1	y_2	y_3
Germany	61	14	82.8
Denmark	53	11	80.6
Italy	43	7	70.8
Spain	40	7	74.2
France	49	24	78.0
United Kingdom	47	21	82.0
Austria	46	10	76.3
Sweden	49	12	81.7
Norway	46	18	78.2
Russia	26	12	65.6

Compiled by the authors based on [World Bank, 2019a](https://data.worldbank.org/indicator/TX.VAL.TECH.MF.ZS?view=chart). High-technology exports (% of manufactured exports). Available from: <<https://data.worldbank.org/indicator/TX.VAL.TECH.MF.ZS?view=chart>> (accessed 01.07.19), [World Bank, 2019b](https://data.worldbank.org/indicator/NV.MNF.TECH.ZS.UN). Medium and high-tech Industry (including construction) (% manufacturing value added). Available from: <<https://data.worldbank.org/indicator/NV.MNF.TECH.ZS.UN>> (accessed 01.07.19.), [World Economic Forum, 2019](http://reports.weforum.org/global-competitiveness-report-2018/). The Global Competitiveness Report 2018. Available from: <http://reports.weforum.org/global-competitiveness-report-2018/?doing_wp_cron=1561957730.9923779964447021484375> (accessed 01.07.19.).

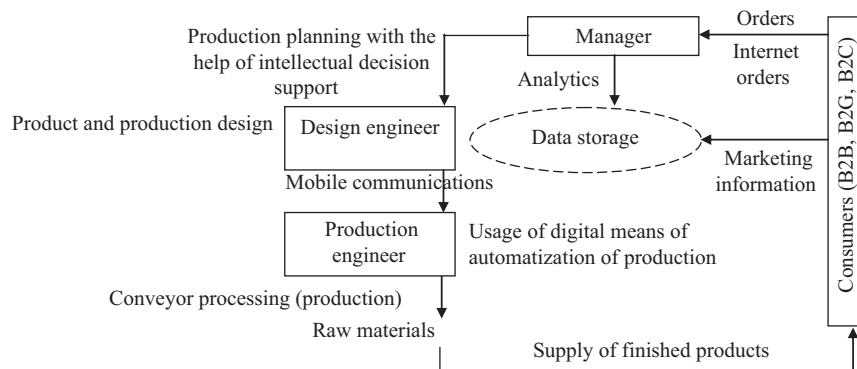


FIGURE 11.2 Scientific concept of passive digital manufacturing.

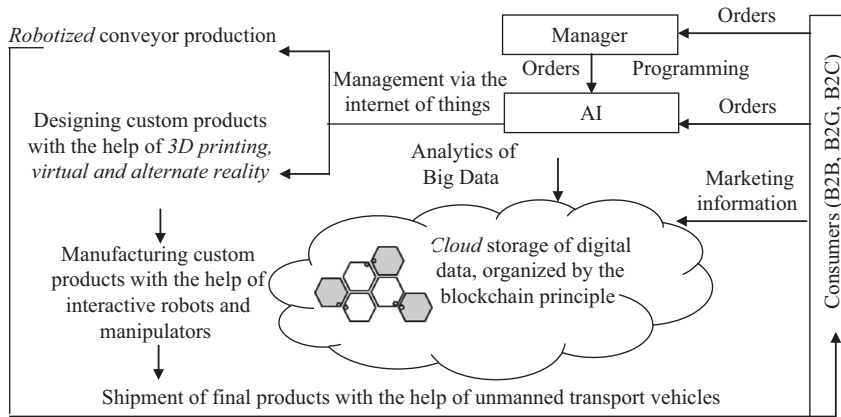


FIGURE 11.3 Scientific concept of active digital manufacturing.

are passed to the production engineer, who transforms raw materials and resources into final products. Only conveyor (mass) production is performed. Final products are supplied to consumers with the usage of transport means that are controlled by humans. Subjects of production could support digital (Internet and mobile) communication between each other and consumers—in particular, for specifying the details of the order and notification of consumers on readiness of the order.

As is shown in Fig. 11.3, the scientific concept of active digital manufacturing envisages that it is controlled (similarly to passive production) by a manager—however, his authority and responsibilities are reduced to the minimum. The manager performs programming of AI—sets the strategic landmarks of the company’s development and forms the logic of decision-making. The manager also collects the orders in nonelectronic (oral and written) form from consumers. AI accepts orders in the electronic form.

Marketing information from consumers goes to cloud storage of digital data, which is organized according to the blockchain principle (for provision of security of data). AI performs analytics of data from the storage with the help of the technologies of Big Data processing. AI controls two directions of industrial production with the help of the Internet of Things:

- Robotized conveyor production for model and mass orders of the consumers;
- Production of custom product for individual orders from consumers. Within this direction, AI performs the design of custom products with the help of 3D print and virtual and alternate reality and manufacturing of custom products with the help of interactive robots and manipulators (under human control).

Final products are supplied to consumers with the help of unmanned transport vehicles. As a result of comparative analysis, we determined the following

differences between the concept of active digital manufacturing and the concept of passive digital manufacturing:

- Fuller automatization and usage of more complex technologies: unlike passive digital manufacturing, during active digital manufacturing, technologies are selected not according to the criterion of accessibility (the more accessible, the better) but according to the criterion of novelty and effectiveness (the newer and more effective, the better);
- Differentiated (bilateral) production: active digital manufacturing allows not only for the conveyor but also for individual production.

The principles of active digital manufacturing are as follows:

- Interactive character of machine control of digital manufacturing in the interests of supporting its higher flexibility for the most precise and the fullest satisfaction of the consumers' needs;
- Reliability and security: during active digital manufacturing, the issues of supporting the stability of digital manufacturing are paid a lot of attention, as high risk of the electronic form of storing the data (loss, damage, and theft) is obvious.

We also determine the following priorities of development of active digital manufacturing:

- Ousting humans from the production process;
- Using more progressive (breakthrough) digital technologies, which are set into the basis of the company's competitiveness.

Thus, passive digital manufacturing is more accessible for industrial companies and is thus more attractive for most of them. At the same time, potential advantages from digital modernization of a company are higher with active digital manufacturing, as the formed digital advantages are more sustainable.

11.4.2 Comparative analysis of the advantages from the development of passive and active digital manufacturing

The results that were obtained in the course of regression analysis are presented in Tables 11.3 and 11.4 to illustrate their representativeness: coefficients a and b in the models of multiple linear regression of type $y = a + b_1 \cdot x_1 + b_2 \cdot x_2 + b_3 \cdot x_3$ (for Table 11.3) and type $y = a + b_4 \cdot x_4 + b_5 \cdot x_5 + b_6 \cdot x_6 + b_7 \cdot x_7 + b_8 \cdot x_8$ (for Table 11.4). Tables 11.3 and 11.4 also reflect the determined target values of the variables that were obtained in the course of optimization modeling (simplex method). The modeling is performed with the help of the function "search for solution."

For data compatibility in both examples, the condition of search for solution is equating y_3 to 95. Tables 11.3 and 11.4 show the values of variables at which the

Table 11.3 Estimate coefficients of regression and example of optimization modeling of active digital manufacturing (condition: $y_3 = 95$).

Variable	Target value	Value in 2018	Growth, %	Coefficients b		
				y_1	y_2	y_3
x_1	106.9	106.9	0.00	0.0567	−0.0237	0.0195
x_2	91.5	12.2	650.38	−0.0326	1.4939	0.2266
x_3	24.9	24.9	0.00	0.2189	−0.1190	0.1823
—	—	—	—	Coefficient a		
y_1	43.4*	46.0	−5.63	34.8909	—	—
y_2	132.1*	13.6	871.56	0.8717	—	—
y_3	95.0*	77.0	23.34	67.6334	—	—

*Set by formula: $y = a + b_1 \cdot x_1 + b_2 \cdot x_2 + b_3 \cdot x_3$.

Table 11.4 Estimate coefficients of regression and example of optimization of modeling of passive digital manufacturing (condition: $y_3 = 95$).

Variable	Target value	Value in 2018	Growth, %	Coefficients b		
				y_1	y_2	y_3
x_4	34.8	34.8	0.00	0.04571	−0.4217	−0.1007
x_5	23.0	23.0	0.00	−0.1585	−0.0715	0.05686
x_6	19.4	19.4	0.00	−0.0361	−0.5107	0.07431
x_7	34.6	11.5	200.61	0.83683	0.9412	0.47579
x_8	14.6	8.2	78.06	1.9532	0.25621	1.09415
				Coefficient a		
y_1	77.8*	46.0	69.15	23.1161	—	—
y_2	36.9*	13.6	171.72	26.901	—	—
y_3	95.0*	77.0	23.34	63.3315	—	—

*Set by formula: $y = a + b_4 \cdot x_4 + b_5 \cdot x_5 + b_6 \cdot x_6 + b_7 \cdot x_7 + b_8 \cdot x_8$.

set condition is achieved (in both cases, there is only one possible solution). Also, growth of target values of variables as compared to their values in 2018 is shown.

The data in Table 11.3 are obtained automatically with the help of the functions “Data analysis: regression” and “Search for solution with simplex method.” With the help of the function “Data analysis: regression” we obtained the following equations of multiple linear regression:

- $y_1 = 34.8909 + 0.0567 \times x_1 - 0.0326 \times x_2 - 0.2189 \times x_3$;
- $y_2 = 0.8717 - 0.0237 \times x_1 + 1.4939 \times x_2 - 0.1990 \times x_3$;
- $y_3 = 67.6334 + 0.0195 \times x_1 + 0.2266 \times x_2 - 0.1823 \times x_3$.

With the help of the function “Search for solution with simplex method” we calculated the target values of variables x_1 , x_2 , x_3 for correspondence to the set condition: $y_3 = 95$. Target value $x_1 = 106.9$, $x_2 = 91.5$, $x_3 = 24.9$. Let us verify the correctness of the received decision—for this we put the obtained target values of the variables into equation $y_3(x_1, x_2, x_3)$. Then we receive: $y_3 = 67.6334 + 0.0195 \times 106.9 + 0.2266 \times 91.5 - 0.1823 \times 24.9 = 95.0$. Therefore the performed calculations are correct—the set condition is observed.

Let us put the obtained target values of the variables into the two remaining functions $y_1(x_1, x_2, x_3)$ and $y_2(x_1, x_2, x_3)$. We obtain the following:

- $y_1 = 34.8909 + 0.0567 \times 106.9 - 0.0326 \times 91.5 - 0.2189 \times 24.9 = 43.4$;
- $y_2 = 0.8717 - 0.0237 \times 106.9 + 1.4939 \times 91.5 - 0.1990 \times 24.9 = 132.1$;

Then we determine the growth of target values of all variables as compared to their factual values in 2018:

- growth $x_1 = 106.9 \times 100\% / 106.9 - 100 = 0.00\%$;
- growth $x_2 = 91.5 \times 100\% / 12.2 - 100 = 650.35\%$;
- growth $x_3 = 24.9 \times 100\% / 24.9 - 100 = 0.00\%$;
- growth $y_1 = 43.4 \times 100\% / 46.0 - 100 = -5.63\%$;
- growth $y_2 = 432.1 \times 100\% / 13.6 - 100 = 871.56\%$;
- growth $y_3 = 95.0 \times 100\% / 77.0 - 100 = 23.34\%$.

As can be seen from Table 11.3, for achieving $y_3 = 95\%$ (growth as compared to 2018—23.34%), it is necessary to preserve x_1 and x_3 at the level of 2018 and to increase x_2 by 650.38% ($91.5 \times 100\% / 12.2 - 100$) up to 91.5. In this case, y_1 will have the value 43.4 (it will decrease by 5.63%, as compared to 2018), and y_2 will be 132.1 (it will increase by 871.56%, as compared to 2018).

The data in Table 11.4 are obtained automatically with the help of the functions “Data analysis: regression” and “Search for solution with simplex method.” With the help of the function “Data analysis: regression” we obtained the following equations of multiple linear regression:

- $y_1 = 23.1161 + 0.04571 \times x_4 - 0.1585 \times x_5 - 0.0361 \times x_6 + 0.83683 \times x_7 + 1.9532 \times x_8$;
- $y_2 = 26.901 - 0.4217 \times x_4 - 0.0715 \times x_5 - 0.5107 \times x_6 + 0.9412 \times x_7 + 0.25621 \times x_8$;
- $y_3 = 63.3315 - 0.1007 \times x_4 + 0.05686 \times x_5 + 0.07431 \times x_6 + 0.47579 \times x_7 + 1.09415 \times x_8$;

With the help of the function “Search for solution with simplex method” we calculated target values of variables x_4 , x_5 , x_6 , x_7 , x_8 for correspondence to the set condition: $y_3 = 95$. The target value $x_4 = 34.8$, $x_5 = 23.0$, $x_6 = 19.4$, $x_7 = 34.6$, $x_8 = 14.6$. Let us verify the correctness of the obtained solution—for this we put the determined target values of the variables into equation $y_3(x_4, x_5, x_6, x_7, x_8)$. We obtain the following: $y_3 = 23.1161 + 0.04571 \times 34.8 - 0.1585 \times 23.0 - 0.0361 \times 19.4 + 0.83683 \times 34.6 +$

$1.9532 \times 14.6 = 95.0$. Therefore the performed calculations are correct—the set condition is observed.

Let us put the determined target values of the variables into the two remaining functions $y_1(x_4, x_5, x_6, x_7, x_8)$ and $y_2(x_4, x_5, x_6, x_7, x_8)$. We obtain the following result:

- $y_1 = 23.1161 + 0.04571 \times 34.8 - 0.1585 \times 23.0 - 0.0361 \times 19.4 + 0.83683 \times 34.6 + 1.9532 \times 14.6$;
- $y_2 = 26.901 - 0.4217 \times 34.8 - 0.0715 \times 23.0 - 0.5107 \times 19.4 + 0.9412 \times 34.6 + 0.25621 \times 14.6$.

Let us determine the growth of target values of all variables as compared to their factual values in 2018:

- growth $x_4 = 34.8 \times 100\%/34.8 - 100 = 0.00\%$;
- growth $x_5 = 23.0 \times 100\%/23.0 - 100 = 0.00\%$;
- growth $x_6 = 19.4 \times 100\%/19.4 - 100 = 0.00\%$;
- growth $x_7 = 34.6 \times 100\%/11.5 - 100 = 200.61\%$;
- growth $x_8 = 14.6 \times 100\%/8.2 - 100 = 78.06\%$;
- growth $y_1 = 77.84 \times 100\%/46.0 - 100 = 69.15\%$;
- growth $y_2 = 36.9 \times 100\%/13.6 - 100 = 171.72\%$;
- growth $y_3 = 95.0 \times 100\%/77.0 - 100 = 23.34\%$.

As can be seen from [Table 11.4](#), for achieving $y_3 = 95\%$ (growth as compared to 2018—23.34%) it is necessary to preserve x_4 , x_5 , and x_6 at the 2018 level, increase x_7 by 200.61% ($34.6 \times 100\%/11.5 - 100$) up to 34.6%, and increase x_8 by 78.06% ($14.6 \times 100\%/8.2 - 100$) up to 14.6%. In this case, y_1 will take the value 77.8 (increase of 69.15%, as compared to 2018), and y_2 will be 36.9 (increase of 171.72%, as compared to 2018).

The obtained and compiled (for all three conditions, which are considered separately—in view of the impossibility of their simultaneous observations) results of the obtained estimate values of independent variables for achieving the target values of dependent variables during passive and active digital manufacturing, as well as the value of their growth, as compared to 2018, are shown in [Table 11.5](#).

As can be seen from [Table 11.5](#), for observing the condition $y_1 = 85$ the independent variables should take the following values during active digital manufacturing: $x_1 = 150.1$ pcs, $x_2 = 12.1\%$, $x_3 = 191.9\%$ (exceeds threshold limit values of 100%). The estimate values of other variables under the set conditions are presented in the similar way. We calculate the direct average of each independent variable for each separate condition, and the following results are obtained:

- Direct average x_1 constitutes 1213 pcs, obtained in the following way:
($150.1 + 106.9 + 106.9$)/3;
- Direct average x_2 constitutes 54.5%, obtained in the following way:
($12.1 + 60.0 + 91.5$)/3;

Table 11.5 Growth of independent variables for achieving the target values of dependent variables during passive and active digital manufacturing.

Type of production	Variable	Estimate value under the condition			Average	Value in 2018	Growth, %
		$y_1 = 85$	$y_2 = 85$	$y_3 = 95$			
Active digital manufacturing	x_1	150.1	106.9	106.9	121.3	106.9	13.459
	x_2	12.1	60.0	91.5	54.5	12.2	346.995
	x_3	191.9	24.9	24.9	80.6	24.9	223.561
	Aggregate growth during active digital manufacturing						584.015
Passive digital manufacturing	x_4	40.8	34.8	34.8	36.8	34.8	5.747
	x_5	23.0	23.0	23.0	23.0	23.0	0
	x_6	19.4	19.4	19.4	19.4	19.4	0
	x_7	23.6	79.5	34.6	45.9	11.5	299.130
	x_8	22.8	37.1	14.6	24.8	8.2	202.846
	Aggregate growth during passive digital manufacturing						507.723

- Direct average x_3 constitutes 80.6%, obtained in the following way:
 $(191.9 + 24.9 + 24.9)/3$;
- Direct average x_4 constitutes 36.8%, obtained in the following way:
 $(40.8 + 34.8 + 34.8)/3$;
- Direct average x_5 constitutes 23.0%, obtained in the following way:
 $(23.0 + 23.0 + 23.0)/3$;
- Direct average x_6 constitutes 19.4%, obtained in the following way:
 $(19.4 + 19.4 + 19.4)/3$;
- Direct average x_7 constitutes 45.9%, obtained in the following way:
 $(23.6 + 79.5 + 34.6)/3$;
- Direct average x_8 constitutes 24.8%, obtained in the following way:
 $(22.8 + 37.1 + 14.6)/3$.

We also calculated the growth of the direct average of estimate values of all independent variables, as compared to 2018, and obtained the following results:

- Growth of estimated value x_1 as compared to the value of this variable in 2018, constituted 13.47%, obtained in the following way: $121.3 \times 100\% / 106.9 - 100$;
- Growth of estimated value x_2 as compared to the value of this variable in 2018 constituted 346.721%, obtained in the following way: $54.5 \times 100\% / 12.2 - 100$;
- Growth of estimated value x_3 as compared to the value of this variable in 2018 constituted 223.561%, obtained in the following way: $80.6 \times 100\% / 24.9 - 100$;

- Growth of estimated value x_4 as compared to the value of this variable in 2018 constituted 5.747%, obtained in the following way: $36.8 \times 100\% / 34.8 - 100$;
- Growth of estimated value x_5 as compared to the value of this variable in 2018 constituted 0%;
- Growth of estimated value x_6 as compared to the value of this variable in 2018 constituted 0%;
- Growth of estimated value x_7 as compared to the value of this variable in 2018 constituted 299.130%, obtained in the following way: $45.9 \times 100\% / 11.5 - 100$.
- Growth of estimated value x_8 as compared to the value of this variable in 2018 constituted 202.846%, obtained in the following way: $24.8 \times 100\% / 8.2 - 100$.

Aggregate growth during active digital manufacturing constituted 584.015% ($13.459 + 346.995 + 223.561$), and during passive digital manufacturing: 507.723% ($5.747 + 0 + 0 + 299.130 + 202.846$). The calculated sums of coefficients $b_1, b_2 \dots b_n$ in the models of multiple linear regression of type $y = a + b_1 \times x_1 + b_2 \times x_2 + \dots + b_n \times x_n$ separately for active and passive digital manufacturing are shown and compared in Fig. 11.4.

As can be seen from Fig. 11.4, the sums of coefficients $b_1 + b_2 + b_3$ in the models of multiple linear regression for active digital manufacturing constituted 0.24 for y_1 , 1.35 for y_2 , and 0.43 for y_3 . In their turn, sums of coefficients $b_1 + b_2 + b_3 + b_4 + b_5$ in the models of multiple linear regression for passive digital manufacturing constituted 2.64 for y_1 , 0.19 for y_2 , and 1.60 for y_3 . On the whole, for all y coefficients b for active digital manufacturing constituted 2.02, for passive digital manufacturing it was 4.44.

Thus, as the sum of coefficients $b_1, b_2 \dots b_n$ for passive digital manufacturing exceeds their sum for active digital manufacturing ($4.44 > 2.02$), and, at the same time, growth of estimate values of independent variables with active digital

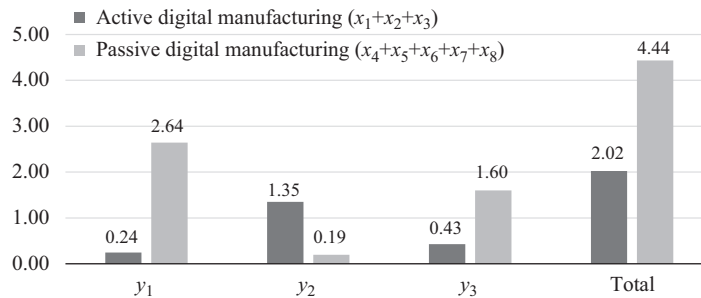


FIGURE 11.4 Sums of coefficients $b_1, b_2 \dots b_n$ in models of multiple linear regression for active and passive digital manufacturing.

manufacturing is higher than growth of the values of independent variables with passive digital manufacturing ($584.015\% > 507.723\%$), hypothesis H_0 is proved.

This means that of two alternative means of digital manufacturing, passive production requires less changes (and, accordingly, effort) and provides higher results—that is, it is more effective, as compared to active digital manufacturing. Therefore active digital manufacturing faces serious problems that hinder its implementation and make the alternative passive digital manufacturing more preferable.

11.4.3 Current problems of starting and implementing active digital manufacturing and their perspective solutions

For determining the current problems of starting and implementing active digital manufacturing and perspectives of solving them, we performed SWOT analysis of the development of this type of digital manufacturing—the results are shown in Table 11.6.

As can be seen from Table 11.6, preconditions (strengths) are connected to active development of infrastructural provision (e.g., conducting R&D and patenting of technologies), presentation of state support for companies that start and implement active digital manufacturing as a priority for the economy, and growing pressure of the market (competition)—the necessity for conducting active digital manufacturing in the interests of ensuring a company's competitiveness in the long term through formation of sustainable competitive advantages.

Table 11.6 SWOT analysis of development of active digital manufacturing.

S	Preconditions (strengths)	• Active development of infrastructural provision • State support • Growing pressure of the market (competition)
W	Problems (weaknesses)	• Problem of formation of the system of machine data collection • Problem of retraining of personnel and training of digital personnel for working with future machines • Problem of financial provision • Problem of risk management
O	Perspectives (opportunities)	• Development of new technologies of machine data collection • Development of the educational market • Flexible financial mechanisms (lease, public–private partnership, integration of companies, etc.) • Development of the market of risk insurance
T	Barriers (threats)	• Separation of the markets of education, labor market, and industrial markets • Institutionalization of the practices of elite active digital manufacturing

We determined the following current problems of starting and implementing active digital manufacturing. The first problem: formation of the system of machine data collection. During active digital manufacturing, the manager is fully excluded from analytics of the company's data, which requires transfer of all data into the electronic form. In addition to this, collection of orders by AI envisages using special templates through entering electronic data by consumers. The perspectives of solving the above problem are connected to creation of the necessary templates and development of new technologies of collection of machine data—for example, technology of computer deciphering of human speech.

The second problem: retraining of personnel and training of digital personnel for working with future machines. Perspectives of solving this problem are connected to development of the educational market. Mastering of digital competencies should be widely accessible—for example, on the basis of remote education.

The third problem: financial provision of active digital manufacturing. Digital modernization of the modern entrepreneurship, aimed at its full automatization, requires large investments, which the companies do not have. The perspectives of solving this problem are connected to application of flexible financial mechanisms: lease, public—private partnership, integration of companies (e.g., clustering), etc.

The fourth problem: risk management of active digital manufacturing. Here we speak primarily of the risk of return of investments into active digital manufacturing (commercialization of breakthrough digital technologies). The perspectives of solving the above problem are connected to development of the market of risk insurance. The government has to provide mass accessibility of services on insuring the investment risks of companies that conduct active digital production. This could be mandatory or voluntary insurance. The government's task is introduction of fixed tariffs or limits on pricing of the cost of insurance services.

However, the barriers (threats) to the establishment and development of active digital manufacturing are connected to separation of the education, labor, and industrial markets (complexity of commercialization of breakthrough digital technologies), as well as the risk of institutionalization of the practices of elite active digital manufacturing (establishment of a false belief of entrepreneurship and society into impossibility of mass conduct of active digital manufacturing).

11.5 Conclusions

Thus, the results of the performed research allow for the conclusion that active digital manufacturing allows for better automatization of the production processes of a modern company and development of production in two directions: conveyor production of standardized (mass) products and custom production of individual products. In both cases, the functions of management are performed by AI. This allows the forming of sustainable competitive advantages and ensuring the company's competitiveness in the long term.

However, by the example of European countries that show the highest level of development of digital society (e.g., characterized by a favorable social environment for the formation and development of the digital economy) it is shown that passive digital production remains a more preferable alternative as compared to active digital manufacturing, which requires more changes (efforts) with lower positive effects.

The reason for the determined contradiction of the conceptual foundations and empirical data in the sphere of active digital manufacturing is the four problems on the path to its start and development: formation of the system of machine data collection, retraining of personnel and training of digital personnel for working with future machines, financial provision, and risk management. This work offers recommendations for solving these determined problems.

It should be concluded that active digital manufacturing is a logical stage in the development of entrepreneurship, and in the course of development of the digital economy this type of digital manufacturing should become dominant (passive digital manufacturing will become unprofitable and will be closed). That is why an important task of the state is overcoming the tendency for the establishment of digital manufacturing's role of elite (rare, implemented only by the largest companies) economic practice.

Despite the probable successful solution to all current problems with the help of the offered recommendations, there is a threat of the formation of an "institutional trap" for active digital manufacturing. This "trap" is connected to voluntary refusal from widely accessible (in the future) active digital manufacturing by most industrial companies due to lack of understanding of its advantages or inclination for their reduction, as well as confidence in excessively high complexity of its creation and realization. This requires a constraint of mass implementation of active digital manufacturing and slowdown of the Fourth Industrial Revolution.

That is why, in the interests of state stimulation of transition of the modern socio-economic systems to Industry 4.0, it is necessary to regulate the social environment not in the direction of development of digital society (increase of digital literacy of the population, distribution of consumer digital technologies and devices, development of online trade, etc.), but in the direction of the provision of public support for active digital manufacturing and its institutionalization as a mass practice in industrial entrepreneurship. Thus, further scientific research in the continuation of this study should be performed within institutional economic science.

Acknowledgment

This research was performed with financial support from the Russian Fund of Fundamental Research within project No. 18-010-00103 A.

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Big Data management and data analysis: Applied solutions in view of the spheres of the modern economy

12

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12.1 Introduction

In the conditions of the “knowledge economy”, information and knowledge are the most valuable resources (objects of economic activities) and products (results of economic activities). The digital economy (“data economy”) increases the flows of data and assigns them with a new function—technology (means of labor), with the help of which economic activities are conducted. This predetermines the high topicality of studying and searching for the means of solving the contradictions that have formed in the modern global practice of management and data analysis.

On the one hand, the volume of collected and accessible (open) data constantly grows, and has become so large that it allows for large-scale research projects not only on the general issues of growth and development of economic systems but also in view of the spheres of the economy. Collection of empirical data on the direction of its specialization is one of the main directions of activities of international organizations. Thus, for example, after adopting the global goals in the sphere of sustainable development in 2015, the UN has been collecting statistical data and calculating the index of sustainable development of the economy.

Collection of marketing information is performed not only by the largest and transnational corporations with marketing departments but also by small and medium-sized companies. When there is no data base—for example, with start-ups—it is possible to use the data from open sources (e.g., social networks). Collection of data is one of the most important components of competitiveness of a modern company. Even at the level of states (countries of the world) there is competition in the sphere of completeness, frequency, and precision of collected statistical data.

On the other hand, the analysis of data is complicated due to their nonsystemic character and imperfection of the technologies of data processing and analytical tools. Most of the results of processing and analysis of data are narrow—they describe separate components of the studied phenomenon or the process, while the picture on the whole remains unclear. Conclusions on the results of analytics are often obscure, which leads to the compilation of incorrect forecasts. The low popularity of analytics complicates the treatment of results and leads to the wrong conclusions.

A typical microeconomic example of ineffective data analytics is determining the reduction of frequency of purchases of a certain type. This provides a substantiation for a reduction of the volume of its production, but the consumer’s logic remains unclear: either consumer preferences changed (in this case, it is necessary to change the technical characteristics of the product), or replacement products for lower price appeared (in this case, it is expedient to reduce the product price), etc. That is why data analytics give a company’s manager a false trust in scientific substantiation of its actions, while he continues to be “blind” in practice.

A macroeconomic example of ineffective analytics of data is determination of the global tendency for hi-tech development of the economy and establishment of the direct and positive dependence of the rate of economic growth on the level of development of technologies and activity of innovative development of model economic systems

(e.g., developed countries). Also, an economic system (e.g., a developing country) could determine in its economy the indirect signs of the advantages of hi-tech development. Based on the results of analytics, the economic system starts the process of digital modernization of its economy, but very often factual results do not meet the expectations—for example, the growth rate of the economy might not increase, but, on the contrary, it might decrease. The reason is the low reliability and fragmentary nature of the initial statistical data, as well as imperfection of their analytics.

Thus, in a modern economy the problem of improvement of the existing practice of management (collection and presentation) and analytics (processing and treatment) of data is very important, because the existing practice does not perform its task—overcoming or significant reduction of uncertainty of the economic activities. Instead of this, the existing practice of management and analytics of data increases uncertainty, causing new questions from managers and national regulators, or creates a false impression of a reduction of uncertainty or belief into the presence of a “road map” of development of economic systems, observation of which leads to unpredictable and often negative consequences.

The purpose of this research is to substantiate this necessity and develop the scientific and practical recommendations for management and analytics of Big Data in view of the spheres of the modern economy. The following tasks are implemented for achieving the formulated goal:

1. Evaluation of the sufficiency of the existing statistical data bases and tools of processing of large arrays of statistical information for analysis of the key spheres of the modern economy;
2. Development of a conceptual model of application of breakthrough digital technologies of management and Big Data analysis for statistical accounting and analytics in various spheres of the modern economy in the conditions of Industry 4.0;
3. Compilation of the algorithm of statistical accounting and analytics for various spheres of the modern economy in the conditions of Industry 4.0 based on breakthrough digital technologies of management and Big Data analysis.

12.2 Literature review

In modern research literature, the issues of management and analysis are paid a great deal of attention. Some researchers focus on data analysis: its growing needs in the conditions of “knowledge economy” and limitations of the existing technologies. Thus, [Hariri et al. \(2019\)](#) note the uncertainty in analysis of Big Data with the help of existing technologies and tools. [Stockinger et al. \(2019\)](#) offer a perspective solution to the problem of the creation of scaled architecture for financial analytics of Big Data with the help of SQL function.

[Silva et al. \(2019\)](#) note the necessity for consideration of the context in which statistical data are collected; the research is performed by the example of consideration

of the European/Brazilian context during the provision of security of data analysis in a cloud. [Singh et al. \(2019\)](#) believe that analytics of data is the central link of the chain of events during management of security in a modern economic system. [ur Rehman et al. \(2019\)](#) point out the key role of analytics of Big Data in the industrial Internet of Things as a perspective cyberphysical system.

[Anejionu et al. \(2019\)](#) studied the system of spatial city data and noted a high need for cloud infrastructure of Big Data for the social and economic analytics of cities. [Cysneiros et al. \(2019\)](#) adapt the Cobb–Douglas model with stochastic limitations to the conditions of Industry 4.0 and come to the conclusion that data analysis in the economy is very important for reproduction of gross product. [Qin and Chiang \(2019\)](#) write that the effectiveness of analytics of data largely determines the capabilities of machine learning. [Raut et al. \(2019\)](#) note that the existing methods of analytics of Big Data should be integrated for sustainable management of business. [Dubey et al. \(2019\)](#) substantiate that Big Data and forecast analytics allow for improvement of the social and ecological sustainability of modern economic systems.

[Carillo et al. \(2019\)](#) show that, depending on the attitude to business analytics, a company's management could be either management that is based on intuition or persons who make rational decisions based on the data. [Fosso Wamba et al. \(2019\)](#) write that in analytics of Big Data in the interests of maximization of efficiency, quantity (volume of processed information) dominates over quality (precision of analytics), which reduces its effectiveness. [Goyal et al. \(2017\)](#) perform an evaluation of the efficiency of an autonomous robot with the help of Rework as a new direction of data analytics in the conditions of Industry 4.0. [Rawat et al. \(2017\)](#) model growth of reliability of program provision with the help of improvement of technologies of data analytics.

[Popkova \(2019\)](#) notes the increase in the need for data analysis due to development of Industry 4.0 and the “knowledge economy.” [Popkova and Sergi \(2019\)](#) note that Industry 4.0 and other innovations (in particular, technologies of management and analytics of Big Data) influence the development of the Russian economy. [Popkova et al. \(2019\)](#) develop a model of state management of the economy based on the Internet of Things, in which an important role belongs to data analysis. [Popkova and Parakhina \(2019\)](#) developed models for managing the global financial system based on AI and noted that its main limitation is imperfection of data analytics.

Other authors have studied Big Data management with the help of technologies of Industry 4.0. These include [Fahmfam and Hamidi \(2019\)](#), who determine the factors that influence the development and management of a “smart city” with the usage of a combination of Big Data, the IoT, and cloud computations. [Babar et al. \(2019\)](#) offer a system of Big Data management for an intellectual city environment based on the IoT with the use of adjusted Hadoop. [Alsaig et al. \(2019\)](#) note the necessity for highly effective Big Data management in the IoT-controlled intellectual development of a city. [Cui et al. \(2019\)](#) perform analytics of Big Data with the help of network calculations, which allows for intellectual management of autonomous transport vehicles in a smart city.

Makkar et al. (2019) consider the latest tendencies and methods of Big Data management. Darmandeh et al. (2019) outline wide capabilities of Big Data management in libraries and information centers. Huang et al. (2019) note the existence of serious problems of application of Big Data for management of production security. Terrazas et al. (2019) use the cloud infrastructure for Big Data management in shops for analytics of elastic computations.

Anshari et al. (2019) control interrelations with customers with analytical support of Big Data in the interests of diversification and personalization of services. El-Kassar and Singh (2019) note the significant influence of Big Data on the implementation of “green” innovations and improvement of organizational indicators. The authors also believe that managers’ devotion to the existing technologies and tools of analytics of large arrays of statistical information restrain the development of new (more effective) practices of personnel management.

Fernández-Caramés et al. (2019) write that the blockchain-based system for inventory and tracking of apps in the sphere of management of supply chains based on Big Data opens the pathway to autonomous storage of Industry 4.0. Domagala (2019) states that technologies of the IoT and Big Data open opportunities for the development of organizations that are based on knowledge management. Cong et al. (2019) consider the imperfection of analytics as the key problem on the path of implementation of innovative models of state management in the age of Big Data. Roy and Roy (2019) note the connection between the IoT and Big Data and suggest using them during the creation of intellectual systems of economic management.

The performed literature overview determined a high level of elaboration of the research problem. The existing scientific publications provide multiple arguments that show the imperfections of the applied technologies and tools of analytics of large arrays of statistical information. Also, the perspectives of development of technologies for Industry 4.0 on Big Data management are discussed.

However, the signs of low effectiveness of the applied technologies and tools of analytics of large arrays of statistical information are fragmented, and only certain possibilities of usage of technologies of Industry 4.0 in Big Data management for solving the narrow applied tasks of certain economic systems are studied.

Therefore there is a need for systemic scientific studies that cover the perspectives of application of technologies of Industry 4.0 for management and analytics of Big Data in view of the spheres of a modern economy, which allow forming a comprehensive concept of this process and offer applied solutions to its current problems, which are to be systematized.

12.3 Materials and method

The authors of this chapter offer a hypothesis that the problem of improving the existing practice of management (collection and presentation) and analytics (processing and treatment) of data cannot be solved within the current (third)

technological mode. First, the collected statistical data are not subject to expanded analytics (H_1). Data are scattered—they are provided by various sources, and selection of the necessary data could not be automatized, as it is not subject to machine logic. For example, a user cannot request all data on the required topic (economic growth, sustainable development, innovations, etc.) with one click, and instead has to select the required data manually. Moreover, the user has to form the necessary compilation data base on the required topic, and data copying is complicated due to differences in the forms of data presentation.

Second, the existing technologies and tools of analytics of large arrays of statistical information are narrow and provide poor opportunities for automatization, which is limited by a set of formulas and possibility of their scaling (H_2). After the necessary data on the selected topic are collected manually, their analysis is also performed manually by the user—due to the uncertainty of the logical ties between the data. The existing formulas of data analysis require adaptation to each specific case, and simple scaling (application of the same formula for large arrays of data) does not allow taking into account the differences between the data. As a result, the analysis is either incomplete (during automatization) or long and labor-intensive (during manual data processing and analysis).

The perspectives of solving the set problem are connected to the transition to the new (fourth) technological mode and application of the technologies of Industry 4.0 for the management and analysis of data. The data have to be treated not only as a large volume of (scattered) information (quantitative characteristics) but as a system of (connected) information (qualitative characteristics)—that is, as Big Data. Management and analysis of Big Data should be flexible and should envisage not just scaling (copying of formulas) but intellectual processing in view of logical interconnections. This research is devoted to verification of the offered hypothesis.

The methodological tools of the research are based on comparative analysis. This method is used for evaluating the completeness and compatibility of the data of statistical accounting in view of the key spheres of a modern economy—agriculture, education, energy, mineral production, financial sphere, health care, trade, and hi-tech. These spheres are given according to the classification of the forms of statistical accounting by the World Bank—the most authoritative and large-scale supplier of open data for official international economics statistics.

The data of other international organizations that conduct statistical accounting of the global economy in view of the distinguished spheres are considered: the European Commission, Global Business Policy Council, the IMD, the Economist Intelligence Unit Limited, WIPO, and the World Economic Forum. The results of the overview of the data of statistical accounting in view of the key spheres of the modern economy are given in table form according to the following model of presentation of the results of an overview of the data of statistical accounting in view of the key spheres of a modern economy (Table 12.1).

The data in Table 12.1 are the authors' own (materials of any secondary sources are not used). Evaluation of the completeness and compatibility of the

Table 12.1 The model of results of data overview presentation.

Spheres	Examples of data (indicators)	Source of data	Units of measurement	The most recent year for which the data are available	Share of the countries for which data for the most recent year are available, %	Countries for which the data are available
Agriculture (1)	E ₁₁	S ₁₁	UM ₁₁	Y ₁₁	D ₁₁	C ₁₁
	E ₁₂	S ₁₂	UM ₁₂	Y ₁₂	D ₁₂	C ₁₂
	E ₁₃	S ₁₃	UM ₁₃	Y ₁₃	D ₁₃	C ₁₃
...	...	...	...	...	...	...
Hi-tech (n)	E _{n1}	S _{n1}	UM _{n1}	Y _{n1}	D _{n1}	C _{n1}
	E _{n2}	S _{n2}	UM _{n2}	Y _{n2}	D _{n2}	C _{n2}
	E _{n3}	S _{n3}	UM _{n3}	Y _{n3}	D _{n3}	C _{n3}

data of statistical accounting of modern economy is performed in view of the distinguished spheres of the economy. Let us consider the logic of evaluation by the example of the sphere of agriculture: if $UM_{11} \neq UM_{12} \neq UM_{13}$; $Y_{11} \neq Y_{12} \neq Y_{13}$; $D_{11} < 90\%$, $D_{12} < 90\%$, $D_{13} < 90\%$; $C_{11} \neq C_{12} \neq C_{13}$ hypothesis H_1 is considered proved, and in the opposite case it is disproved.

Then we determine the limitations of the existing tools of analytics of large arrays of statistical information using the example of Excel (as a widely accessible software according to the criterion of cost and simplicity of usage) at each stage of the process of management and analytics of data: collection of data, processing of data, and drawing of results. The current needs of analytics are determined, and possibilities of satisfying them with the help of the existing analytics tools of large arrays of statistical information with the example of Excel are assessed. If there are limitations or essential impossibility to satisfy any needs of analytics with the help of the existing analytics tools of large arrays of statistical information by the example of Excel, hypothesis H_2 is considered proved, and in the opposite case it is disproved.

Also, the causes of complexity or impossibility of satisfaction of the need (barriers and conditions of satisfaction) are determined with the help of the existing analytics tools of large arrays of statistical information with the example of Excel. The possibilities of satisfying all needs with the help of breakthrough digital technologies of Industry 4.0 on management and analytics of Big Data are determined, and perspective tools (specific technologies) are offered.

12.4 Results

12.4.1 Evaluation of the sufficiency of the existing statistical data bases and tools for processing of large arrays of statistical information for analysis of the key spheres of the modern economy

Let us perform an evaluation of the sufficiency of the existing statistical data bases and tools for processing of large arrays of statistical information for analysis of the key spheres of a modern economy. For this, we use the obtained results in the course of an overview of the data of statistical accounting in view of the key spheres of a modern economy (Table 12.2).

In Table 12.2, the authors perform the selection and systematization of the existing statistical data from various sources and perform analysis of these data: the most recent year for which the data are available, share of the countries for which data for the most recent year are available, and countries for which the data are available are determined. As is shown in Table 12.2, in the sphere of agriculture the following data are available in the official international statistics:

Table 12.2 Results of data collection.

Sphere	Examples of data	Source of data	Units of measurement	The most recent year for which the data are available	Share of the countries for which data for the most recent year are available	Countries for which the data are available
Agriculture	Agriculture, forestry, and fishing, value added	World Bank	% of GDP	2018	5%	254
	Food production index	World Bank	Shares of 1 (2004–2006 = 100)	2016	80%	249
	The Global Food Security Index	The Economist Intelligence Unit Limited	Rank, score	2018	100%	121
Education	Government expenditure on education	World Bank	% of GDP	2018	1%	228
	Labor force Pillar 6: skills	World Bank	People	2018	100%	234
		World Economic Forum	Points 0–100 (best)	2018	100%	140
	Training and education	IMD	Rank	2018	100%	63
Energy and mineral production	Fuel exports	World Bank	% of merchandise exports	2018	30%	186
	Investment in energy with private participation	World Bank	Current US\$	2018	50%	85

(Continued)

Table 12.2 Results of data collection. *Continued*

Sphere	Examples of data	Source of data	Units of measurement	The most recent year for which the data are available	Share of the countries for which data for the most recent year are available	Countries for which the data are available
Financial sphere	Energy intensity level of primary energy	World Bank	MJ/\$2011 PPP GDP	2015	100%	175
	Electric power consumption	World Bank	kWh per capita	2018	1%	128
	Foreign direct investment, net inflows	World Bank	BoP, current US\$	2018	85%	256
	Foreign Direct Investment Confidence Index	Global Business Policy Council	Score (scale of 3)	2019	100%	25
	Pillar 9: financial system	World Economic Forum	Points 0–100 (best)	2018	100%	140
Healthcare	Mortality rate, infant	World Bank	People, per 1000 live births	2017	100%	248
	Life expectancy at birth, total	World Bank	Years	2017	95%	251
	Pillar 5: health	World Economic Forum	Points 0–100 (best)	2018	100%	140
Trade	High-technology exports	World Bank	Current US\$	2018	30%	195
	Logistics performance index	World Bank	Points (1 = low to 5 = high)	2016	95%	147

Hi-tech	Net barter terms of trade index	World Bank	2000 = 100	2017	99%	134
	Lead time to import, median case	World Bank	Days	2016	85%	122
	High-technology exports	World Bank	% of manufactured exports	2018	40%	116
	I-DESI	European Commission	Rank, %	2019	100%	28
	Digital competitiveness index	IMD	Rank	2018	100%	63
	Global competitiveness index 4.0	World Economic Forum	Points 0–100 (best)	2018	100%	140
	Global Innovation Index	WIPO	Rank, score	2018	100%	65

Developed and compiled by the authors based on *European Commission, 2019. I-DESI*. <<https://ec.europa.eu/digital-single-market/en/desi>> (accessed 25.07.19.), *Global Business Policy Council, 2019. Foreign Direct Investment Confidence Index*. <<https://www.atkearney.com/foreign-direct-investment-confidence-index>> (accessed 25.07.19.), *IMD, 2019. Digital competitiveness index*. <<https://www.imd.org/wcc/world-competitiveness-center-rankings/world-digital-competitiveness-rankings-2018>> (accessed 25.07.19.), *The Economist Intelligence Unit Limited, 2019. The Global Food Security Index*. <<https://foodsecurityindex.eiu.com>> (accessed 25.07.19.), *WIPO, Global Innovation Index, 2019*. <<https://www.wipo.int/publications/en/details.jsp?id=4330>> (accessed 25.07.19.), *World Bank, 2019. Indicators*. <<https://data.worldbank.org/indicator>> (accessed 25.07.19.), *World Economic Forum, 2019. The Global Competitiveness Report 2017–2018*. <<https://www.weforum.org/reports/the-global-competitiveness-report-2017-2018>> (accessed 25.07.19.).

- Indicator Agriculture, forestry, and fishing, value added: calculated by the World Bank, measured in % of GDP. The most recent year for which the data are available: 2018. Share of the countries for which data for the most recent year are available: 5%. Countries for which the data are available: 254;
- Index Food production index: calculated by the World Bank, measured in shares of 1 (2004–2006 = 100). The most recent year for which the data are available: 2016. Share of the countries for which data for the most recent year are available: 80%. Countries for which the data are available: 249;
- Index The Global Food Security Index: calculated by the Economist Intelligence Unit Limited, measured in rank, score. The most recent year for which the data are available: 2018. Share of the countries for which data for the most recent year are available: 100%. Countries for which the data are available: 121.

In the sphere of education in the official international statistics the following data are available:

- Indicator Government expenditure on education: calculated by the World Bank, measured in % of GDP. The most recent year for which the data are available: 2018. Share of the countries for which data for the most recent year are available: 1%. Countries for which the data are available: 228;
- Indicator Labor force: calculated by the World Bank, measured in people. The most recent year for which the data are available: 2018. Share of the countries for which data for the most recent year are available: 100%. Countries for which the data are available: 234;
- Index Pillar 6: Skills: calculated by the World Economic Forum and presented within the Global Competitiveness Report, measured in points 0–100 (best). The most recent year for which the data are available: 2018. Share of the countries for which data for the most recent year are available: 100%. Countries for which the data are available: 140;
- Index Training and education: calculated by the IMD, measured in rank. The most recent year for which the data are available: 2018. Share of the countries for which data for the most recent year are available: 100%. Countries for which the data are available: 63.

In the sphere of energy and mineral production, the following data are available in the official international statistics:

- Indicator Fuel exports: calculated by the World Bank, measured in % of merchandise exports. The most recent year for which the data are available: 2018. Share of the countries for which data for the most recent year are available: 30%. Countries for which the data are available: 186;
- Indicator Investment in energy with private participation: calculated by the World Bank, measured in current USD. The most recent year for which the data are available: 2018. Share of the countries for which data for the most recent year are available: 80%. Countries for which the data are available: 85;

- Indicator Energy intensity level of primary energy: calculated by the World Bank, measured in MJ/\$2011 PPP GDP. The most recent year for which the data are available: 2015. Share of the countries for which data for the most recent year are available: 100%. Countries for which the data are available: 175;
- Indicator Electric power consumption: calculated by the World Bank, measured in kWh per capita. The most recent year for which the data are available: 2018. Share of the countries for which data for the most recent year are available: 1%. Countries for which the data are available: 128.

In the financial sphere of the economy, the following data are available in the official international statistics:

- Indicator Foreign direct investment, net inflows: calculated by the World Bank, measured in BoP, current. The most recent year for which the data are available: 2018. Share of the countries for which data for the most recent year are available: 85%. Countries for which the data are available: 256;
- Index Foreign Direct Investment Confidence Index: calculated by the Global Business Policy Council, measured by score (scale of 3). The most recent year for which the data are available: 2019. Share of the countries for which data for the most recent year are available: 100%. Countries for which the data are available: 25 (presented in the form of the rating of top 25 countries);
- Index Pillar 9: Financial system: calculated by the World Economic Forum and presented within the Global Competitiveness Report, measured in points 0–100 (best). The most recent year for which the data are available: 2018. Share of the countries for which data for the most recent year are available: 100%. Countries for which the data are available: 140.

In the sphere of healthcare, the following data are available in the official international statistics:

- Indicator Mortality rate, infant: calculated by the World Bank, measured in people, per 1000 live births. The most recent year for which the data are available: 2017. Share of the countries for which data for the most recent year are available: 100%. Countries for which the data are available: 248;
- Indicator Life expectancy at birth, total: calculated by the World Bank, measured in years. The most recent year for which the data are available: 2017. Share of the countries for which data for the most recent year are available: 95%. Countries for which the data are available: 251;
- Index Pillar 5: Health: calculated by the World Economic Forum and presented within the Global Competitiveness Report, measured in points 0–100 (best). The most recent year for which the data are available: 2018. Share of the countries for which data for the most recent year are available: 100%. Countries for which the data are available: 140.

In the sphere of trade, the following data are available in the official international statistics:

- Indicator High-technology exports: calculated by the World Bank, measured in current USD. The most recent year for which the data are available: 2018. Share of the countries for which data for the most recent year are available: 30%. Countries for which the data are available: 195;
- Index Logistics performance index: calculated by the World Bank, measured in points (1 = low to 5 = high). The most recent year for which the data are available: 2016. Share of the countries for which data for the most recent year are available: 95%. Countries for which the data are available: 147;
- Index Net barter terms of trade index: calculated by the Economist Intelligence Unit Limited, measured in 2000 = 100. The most recent year for which the data are available: 2017. Share of the countries for which data for the most recent year are available: 99%. Countries for which the data are available: 134;
- Index Lead time to import, median case: calculated by the World Bank, measured in days. The most recent year for which the data are available: 2016. Share of the countries for which data for the most recent year are available: 85%. Countries for which the data are available: 122.

Thus, in all the above spheres of the economy the data have different measuring units ($UM_{11} \neq UM_{12} \neq UM_{13}$, etc.), the most recent years for which the available data do not coincide ($Y_{11} \neq Y_{12} \neq Y_{13}$, etc.), shares of countries for which data for the most recent year are available do not reach 90% in a lot of cases ($D_{11} < 90\%$, $D_{12} < 90\%$, $D_{13} < 90\%$ etc.), countries for which the data are available are different in all cases ($C_{11} \neq C_{12} \neq C_{13}$ etc.). Therefore, the existing data are incomplete and incomparable, which hinders their analysis—this proves hypothesis H_1 .

12.4.2 The conceptual model of application of breakthrough digital technologies of management and Big Data analysis for statistical accounting and analytics in various spheres of the modern economy in the conditions of Industry 4.0

Limitations of the existing analytics tools of large arrays of statistical information using the example of Excel are determined in Table 12.3; the perspectives of their overcoming with the help of breakthrough technologies of Industry 4.0 are also determined.

The data in Table 12.3 are the authors' development (materials of secondary source are not used)—they are obtained through analysis of the data from Table 12.2, which was performed using Excel in the following way:

- Structuring (sorting and classification) of data according to the set criterion (countries of a certain region or category that show the highest or lowest

Table 12.3 Limitations of the existing tools of large arrays of statistical information analytics.

Stage	Need for analytics	The existing analytics tools of large arrays of statistical information using the example of Excel		Breakthrough digital technologies of management and Big Data analysis	
		Possibility of satisfying the need (condition, barriers)	Cause of complexity or impossibility of satisfying the need	Possibility of satisfying the need	Tool of satisfying the need (and eliminating the barrier)
collection of data	Structural, trend, and comparative analysis, compilation of ratings Cluster analysis	No	Completeness (deficit) of data	Yes	AI
		No	Deficit of data on Industry 4.0	Yes	MapReduce, Hadoop
processing of data	Factor analysis	Yes (time-consuming)	Logical connections between the data are determined	Yes	Blockchain, NoSQL
	Calculation of indices	Yes (time-consuming)	Incompatibility of data Scattered data	Yes Yes	Language of programming R, AI
	Regression and correlation analysis	Yes (time-consuming)	Incompleteness of data	Yes	
	Scenario analysis	Yes (time-consuming)	Necessity for “manual” start, absence of models	Yes	
results	Systemic analysis and qualitative treatment of results	Yes (time-consuming)	Inflexibility of presentation of data	Yes	Cloud technologies, alternate reality
			Uncertainty of the economic sense of data	Yes	AI

values of the indicators) with the help of the function “sorting data as to increase/decrease”;

- Trend analysis (calculating the ratio of the value of the indicator in the current year to its value in the basic year, for each country) with the help of the manually set formula: x_i/x_0 ;
- Comparative analysis (comparing the values of various indicator between the countries) with the help of the manually set formula: x_i/x_j and formula $x_i - x_j$ and variation analysis with the function “STANDARDDEV” and “AVERAGE”;
- Compilation of ratings (selection of countries that are characterized by the values of the indicators in the set intervals) with the help of various manually set formulas;
- Cluster analysis (calculating the ratio of data in various spheres of economy—for example, service sphere, agriculture, industry, and Industry 4.0) with the help of the manually set formula: x_i/x_j after manual sorting of data;
- Factor analysis (determining the influence of various factors on the values of the indicators and the differences in this influence among countries of the world) with the help of regression and correlation analysis;
- Calculating indices (e.g., the index of development of Industry 4.0 as a totality of the indicators of innovations and hi-tech);
- Regression analysis (compiling the models of paired and multiple linear regression) with the help of the function “Data analysis: regression”;
- Correlation analysis (calculating correlation dependence of some indicators from other indicators) with the help of the “CORREL” function;
- Scenario analysis (compiling the forecasts of the indicators’ change in the future under the influence of the selected factors) with the help of function “Search for solution with simplex method”;
- Systemic analysis and qualitative treatment of the results with the help of the creation of graphs.

Here are the examples of mathematical calculations in Excel based on the existing statistical data in the sphere of hi-tech. The dependent variable is hi-tech export, and the independent variable is the Global Innovation Index. The objects for analysis are the top-10 countries as to the value of the Global Innovation Index in 2019. Let us perform the research in dynamics—for 2015 and 2019. The initial data are given in Table 12.4, with results of the performed trend analysis, correlation analysis, and variation analysis.

The results of the regression analysis are presented in Fig. 12.1 (reduced analysis in the form of a regression curve based on the 2015 data) and Table 12.5 (expanded regression analysis for 2015).

The above example showed three most important drawbacks (limitations) of the existing statistical data and possibilities of their analysis. First, weak mathematical connection of the indicators (negative correlation in 2019) is determined—despite their strong logical connection—which complicates qualitative

Table 12.4 Statistics of high-tech and their analysis.

Country	2015			2018			Trend	
	High-technology exports, % of manufactured exports (y_0)	Global Innovation Index, points 1–100 (x_0)	Correlation, %	High-technology exports, % of manufactured exports (y_1)	Global Innovation Index, points 1–100 (x_1)	Correlation, %	y_1/y_0	x_1/x_0
Switzerland	26.83	68.30	9.64	10.99	68.40	– 3.49	0.41	1.00
Netherlands	18.02	61.58		18.58	63.32		1.03	1.03
Sweden	14.25	62.40		12.48	63.08		0.88	1.01
United Kingdom	20.81	62.42		20.71	60.13		1.00	0.96
Singapore	49.27	59.36		49.17	59.83		1.00	1.01
United States	18.99	60.10		13.82	59.81		0.73	1.00
Finland	8.72	59.97		7.32	59.63		0.84	0.99
Denmark	15.96	57.70		11.24	58.39		0.70	1.01
Germany	16.66	57.05		13.90	58.03		0.83	1.02
Ireland	26.76	59.13		19.17	57.17		0.72	0.97
Israel	19.66	53.54		13.84	56.79		0.70	1.06
South Korea	26.84	56.26		14.18	56.63		0.53	1.01
Japan	16.78	53.97		13.80	54.95		0.82	1.02
Average	21.50	59.37		16.86	59.70		0.78	1.01
Standard deviation	9.88	3.93	–	10.36	3.56	–	–	–
Variation coefficient, %	45.92	6.61	–	61.42	5.96	–	–	–

Compiled by the authors based on *WIPO, Global Innovation Index, 2019*. <<https://www.wipo.int/publications/en/details.jsp?id=4330>> (accessed: 25.07.19.), World Bank, 2019. Indicators. <<https://data.worldbank.org/indicator>> (accessed: 25.07.19.).

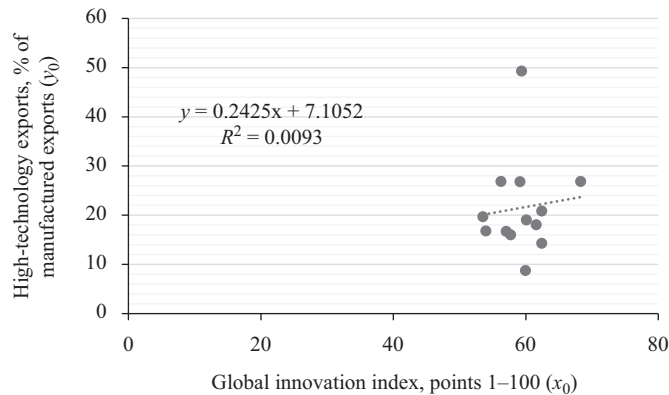


FIGURE 12.1 Regression curve of the statistics of hi-tech in 2015.

interpretation of the results of analysis and does not allow for its automatization. Second, the data for the Global Innovation Index are available only for 2019, and for hi-tech export—only for early 2018 (late 2017), which did not allow for more recent (2019) research. Third, all necessary data are available only for top-performing countries, while for other countries they are lacking—which did not allow for comparative and cluster analysis.

As shown in Table 12.3, the modern analytics have the following needs in the distinguished spheres of the economy:

- The need for structural, trend, and comparative analysis of data and compilation of ratings. It cannot be satisfied with the help of the existing analytics tools of large arrays of statistical information (e.g., Excel) due to incompleteness (deficit) of data. This limitation could be overcome with AI;
- The need for cluster analysis. It cannot be satisfied with the help of the existing analytics tools of large arrays of statistical information (e.g., Excel) due to a deficit of data on Industry 4.0. Comparison of economic phenomena and processes on the whole in the studied sphere and its segment Industry 4.0 is impossible. This limitation could be overcome by breakthrough digital technologies of management and Big Data analysis: MapReduce and Hadoop;
- Need for factor analysis. It could be satisfied with the help of the existing analytics tools of large arrays of statistical information (e.g., Excel), but with high labor intensity—due to the fact that logical connections between the data are not determined. This limitation could be overcome by breakthrough digital technologies of management and Big Data analysis: blockchain and NoSQL;
- Need for calculation of indices. It could be satisfied with the help of the existing analytics tools of large arrays of statistical information (e.g., Excel), but with high labor intensity—due to incompatibility of the data (differences

Table 12.5 Regression analysis of statistics of hi-tech in 2019.

Regression statistics						
Multiple R	0.0349					
R ²	0.0012					
Adjusted R ²	−0.0896					
Standard error	10.8099					
Observations	13					
Dispersion analysis						
	Df	SS	MS	F	Significance F	
Regression	1	1.5717	1.5717	0.0134	0.9098	
Residue	11	1285.3883	116.8535			
Total	12	1286.9600				
	Coefficients	Standard error	t-Stat	P-value	Lower 95%	Upper 95%
Y-intercept	22.9367	52.4692	0.4371	.6705	−92.5474	138.4207
x ₁	−0.1018	0.8774	−0.1160	.9098	−2.0328	1.8293

in years and units of measuring). This limitation could be overcome by breakthrough digital technologies of management and Big Data analysis: languages of programming R and AI;

- Need for regression and correlation analysis. It could be satisfied with the help of the existing analytics tools of large arrays of statistical information (e.g., Excel), but with high labor intensity—due to incompleteness of data determination (only resulting indices are available with uncertainty of the initial data). The determined limitation could be overcome with breakthrough digital technologies of management and Big Data analysis: language of programming R and AI;
- Need for scenario analysis. It could be satisfied with the help of the existing analytics tools of large arrays of statistical information (e.g., Excel), but with high labor intensity—due to the necessity for “manual” start and absence of the models of forecasts and scenarios. This limitation could be overcome with breakthrough digital technologies of management and Big Data analysis: language of programming R and AI;
- Need for systemic analysis and qualitative treatment of results. It could be satisfied with the help of the existing analytics tools of large arrays of statistical information (e.g., Excel), but with high labor intensity—due to inflexibility of data presentation (the form of presentation of data is not selected, and their combination and selective presentation are impossible) and uncertainty of the economic sense of the data. This contradiction could be overcome with the breakthrough digital technologies of management and Big Data analysis: cloud technologies and alternate reality.

The determined contradictions show the necessity for adaptation of the breakthrough digital technologies of management and Big Data analysis to the needs of statistical accounting and analytics in various spheres of the modern economy in the conditions of Industry 4.0. For this, we developed a conceptual model of application of breakthrough digital technologies of management and Big Data analysis for statistical accounting and analytics in various spheres of a modern economy in the conditions of Industry 4.0 (Fig. 12.2).

As is seen from Fig. 12.2, Big Data in a certain sphere are stored in the “cloud” and organized by the principle of blockchain, which allows storing them over a long period of time (20 + years) and correcting their copies with preservation of the initial data. Blockchain and NoSQL are used for determining logical connections between data (hierarchy, interdependence, etc.: shown by solid and dotted lines), which simplifies their further analysis. AI performs comparative, trend, and structural analysis of data. The determined trends, compiled ratings, and calculated indices are presented to mass users (to all interested parties in open access).

Also, there is a need for new data, which are sought from suppliers—for example, international organizations (World Bank, etc.). During integration of AI with the language of programming R the calculation of indices, regression and

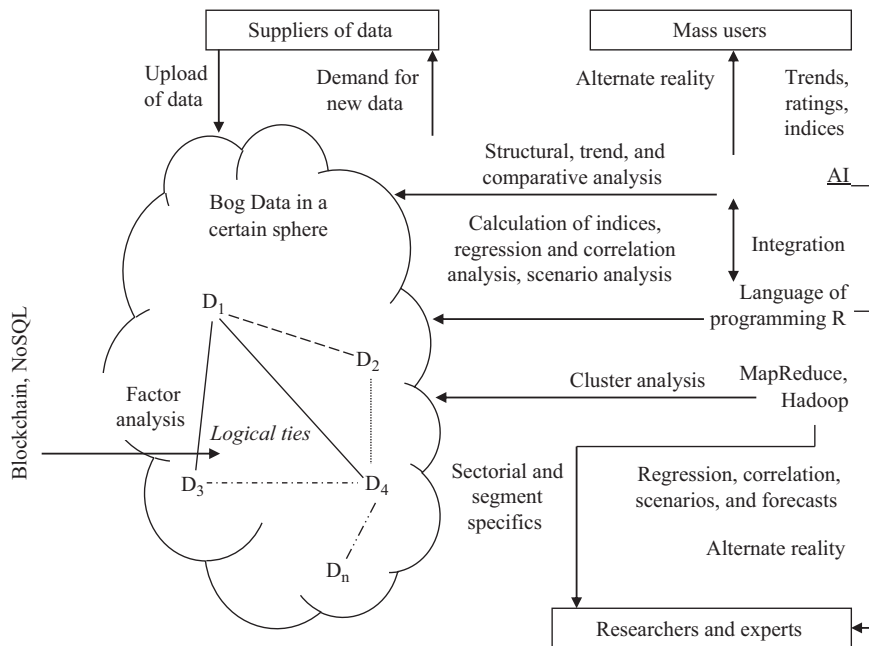


FIGURE 12.2 Model of Big Data analysis in the conditions of Industry 4.0.

correlation analysis, and scenario analysis are performed. Its results (regression, correlation, scenarios, and forecasts) are provided—with the help of alternate reality—to researchers and experts (upon special request). Technologies MapReduce and Hadoop are used for cluster analysis—their results (sectorial and segment specifics) are also presented to researchers and experts (upon special request).

12.4.3 The algorithm of statistical accounting and analytics for various spheres of a modern economy in the conditions of Industry 4.0 based on breakthrough digital technologies of management and Big Data analysis

The developed model reflects the process of analytics of Big Data with the help of breakthrough technologies of Industry 4.0. It belongs to the normative economy, showing the organization of the process of management and data analysis. For practical implementation of the offered model (positive economy) we offer the following algorithm of statistical accounting and analytics for various spheres of the modern economy in the conditions of Industry 4.0 based on breakthrough digital technologies of management and Big Data analysis (Fig. 12.3).

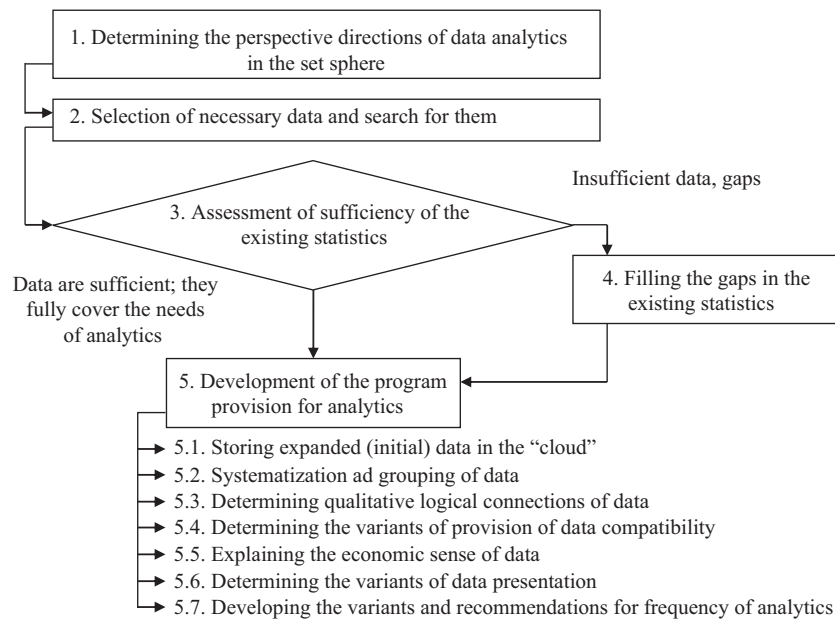


FIGURE 12.3 Algorithm of statistical accounting and Big Data analysis in conditions of Industry 4.0.

As is shown in Fig. 12.3, the first stage of the developed algorithm is determining the perspective directions of analytics of data in the set sphere. For example, the perspective directions in the sphere of hi-tech are as follows:

- Comparison of the characteristics of business activity (profitability, efficiency, share of export, etc.) in low-tech, medium-tech, and hi-tech entrepreneurship;
- Analysis of the influence of development of Industry 4.0 (volume of created added value, share in the structure of entrepreneurship, share in export, etc.) on the macroeconomic indicators (competitiveness, economic growth);
- Comparison of activity of application of various breakthrough digital technologies of Industry 4.0 in society, entrepreneurship, and state management.

The second stage envisages selection of the necessary data and the search for them. For example, in the hi-tech sphere, the following data are necessary within the following perspective directions: characteristics of business activity of entrepreneurship according to the type of performance, indicators of development of Industry 4.0, and indicators of activity of application of various breakthrough digital technologies of Industry 4.0. At the third stage, sufficiency of the existing statistics is assessed. If the data are sufficient, but there are certain gaps (e.g., the modern statistics lacks the indicators of activity of application of various

breakthrough digital technologies of Industry 4.0), at the fourth stage the determined gaps are filled by collecting the absent statistical data.

Then, if the data are sufficient, they fully cover the needs of analytics, and the fifth stage envisages the development of program provision for analytics:

- Preservation of expended data in the “cloud” storage: they are available upon request;
- Systematization and grouping of data (according to various classification features—e.g., types of performance);
- Determining qualitative logical connections between the data (e.g., selection of all indicators that are connected to innovations);
- Determining the variants of provision of compatibility of data (data conversion with the help of special indices, coefficients, and ratings);
- Explaining the economic sense of data (for AI in the logical form and for the user in a descriptive form);
- Determining the variants of data presentation (e.g., in a table, graphic, or other form, through their sorting by the user, etc.);
- Development of variants and recommendations according to frequency of analytics (e.g., quarterly or yearly).

12.5 Conclusions

It is possible to conclude that the offered hypothesis is proved: the existing technologies and tools of analytics of large arrays of statistical information (e.g., Excel) do not satisfy all the needs of modern analytics and are peculiar for significant limitations due to incompleteness of data, deficit of data on Industry 4.0, uncertainty of logical connections between data, incompatibility of data, scattered character of data, necessity for “manual” start, absence of models, inflexibility of data presentation, and uncertainty of the economic sense of data.

These limitations could be overcome by application of the technologies of Industry 4.0 for management and analytics of data—namely, AI, cloud technologies and blockchain, alternate reality, and technologies MapReduce, Hadoop, NoSQL, and language of programming R. For successful implementation of the above technologies into modern economic practice, we have developed and presented the model of application of breakthrough digital technologies of management and Big Data analysis for statistical accounting and analytics in various spheres of a modern economy in the conditions of Industry 4.0 and the algorithm of statistical accounting and analytics for various spheres of a modern economy in the conditions of Industry 4.0 based on breakthrough digital technologies of management and Big Data analysis.

Concluding the research, it should be noted that it has illustrated an urgent need for application of breakthrough digital technologies of Industry 4.0 in the process of management and analytics of Big Data (shown in view of the key

spheres of the modern economy). However, we have selected and outlined the perspective technologies. Though they are being developed, and certain of them (e.g., cloud technologies and blockchain) are being tested, it is necessary to adapt them to the needs of the management and analytics of Big Data.

Development of a modern economic science and scientific approach to state and corporate management is restrained by imperfection of management and analytics of Big Data. The key problem is the elite character of analytics—it is performed only by its developers, while mass users have access only to certain results of Big Data analysis. This allows evaluating the state of affairs in the economy (e.g., position in the rating), but does not allow for determining causal connections and selecting the optimal regulation mechanisms.

The perspectives of improving the practice of management and analytics of Big Data are connected to the transition of data sources (e.g., international organizations) from suppliers of final data to suppliers of software provision for their specialized analytics. For example, the World Bank could issue its own (probably, paid) app/program that would allow for large-scale scientific research on the basis of its statistical data base, which is integrated with other existing data bases in view of the spheres of economy.

This will allow for rationalization of economic activities and increase its effectiveness. When performing further research on the basis of the presented economic recommendations and the offered organizational model and algorithm, it is recommended to develop technical solutions to the actualized problems of management and analytics of Big Data. This will probably require multidisciplinary research involving representatives from the economic, mathematical, and technical sciences.

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Infusion–diffusion process-based modeling and profit estimation for manufacturing industries

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13.1 Introduction

Innovation is one of the most imperative components for organizations in the process of introducing new products and services into the market. It is a crucial step that begins with the introduction of an idea, its implementation, and finally studying whether that particular innovation was truly innovative enough to leave its impact on the market or not. But how can one evaluate the success of an innovation? Generally it is assumed that an innovation will flourish when all its

would-be adopters will adopt the product and use them efficiently. Or will it? We shall examine this in the subsequent sections.

Earlier the success of any innovation was evaluated on the basis of the number of adopters that are taking up the product. However, there has been a gradual change in that trend since then. Nowadays, organizations are more concerned with the attainment of desired benefits from the success of an innovation; or better described as successful exploitation of the new knowledge. According to Schumpeter's Innovation Theory of Profit, "The main function of an entrepreneur is to introduce innovations and the profit in the form of reward is given for his performance." According to Schumpeter, "Innovation refers to any new policy that an entrepreneur undertakes to reduce the overall cost of production or increase the demand for his products" (<https://businessjargons.com/schumpeters-innovation-theory-of-profit.html>). Therefore to exploit the maximum potential that an innovation has to offer, industries must also concentrate on a few other aspects and policies, which will ensure the maximum reliability of the product and hence increased profits. This can be achieved by wisely allocating a significant amount of resources when the product is in its experimental phase. Expending on R&D and concurrently introducing a new innovation will be able to provide fruitful results in terms of a reliable product. Hence, an industry has to be shrewd and perspicacious when it comes to spending its funds on R&D and in introducing innovation in a market which is precisely a combination of infusion and diffusion processes.

The term infusion literally means adding or introducing a new element into something to make it better. Research by Eder and Igbaria (2001) proposed that adoption of an innovation in its initial phase will depend on both diffusion and the internal deployment of resources. Therefore industries also have to consider the engineering aspects with the existing marketing aspects and thereby manage their funds judiciously. Hence it is equally crucial to inspect the manufacturing aspect of the product as well as determination of sales of the product.

The process of diffusion, as defined by Rogers (1983) examines how a new idea is spread (diffused) among the members of a social system through certain channels. However, it is not that simple to put an innovation to its final use from the point that it was first originated because the nature of communication networks and word of opinion leaders play a vital part in determining whether the innovation will be adopted or not. Therefore organizations have to face a common problem of deciding how to pace the rate of the infusion and diffusion process so that an effective innovation can be brought to the masses successfully. An enormous amount of research has been done in the discipline of innovation diffusion theory. One of the most famous and widely used diffusion models was created by F.M. Bass (1969) which categorizes adopters into innovators and imitators—based on their degree of responsiveness once the information about an innovation reaches them. Adoption behavior for successive generations of technological products has been studied by Norton et al. (1987). Mahajan and Muller (1996) presented a framework to study the adoption and substitution process for durable

technological innovations. The effects of various marketing mix variables on the diffusion process have been studied by Bass et al. (2000). A generalized approach to the innovation and diffusion process was given by Anand et al. (2014) in which product awareness and product adoption were studied jointly. Anand et al. (2016) developed a predictive model using customer satisfaction as a metric of how products and services were offered by industries. The effects of awareness and motivation on adoption behavior have been intricately modeled by Anand et al. (2016) to give a unified approach for the adoption process. Agarwal et al. (2017) developed a systematic approach to model the sales for an intergenerational diffusion process. A generalized stochastic diffusion model using Itô's process is studied by Singhal et al. (2019) which jointly discusses the awareness of the product and final adoption of an innovation.

In addition to the efforts and resources that are spent on the improvement of the infusion and diffusion rate, it is insufficient to focus solely on the presale factors of a product such as brand, reputation, and price. In today's demanding world, where competition is tough, it is a very delicate process to convince a consumer to choose a particular product when the competing brands are offering products with almost identical features. Most of the time, it happens that a customer has to encounter a variance between the product's actual performance and his own anticipated expectation. Therefore, naturally, the customer would seek some kind of assurance from the manufacturer if such a conflicting scenario were to occur. And thereby, the role of the warranty comes into being, which not only stimulates the willingness of the consumer to buy the product but also brings a positive impact to the industrial profit. This chapter is an attempt to understand how giving an additional service such as a warranty could turn out to be beneficial for industries despite the already existing efforts that are put into the infusion process. The remainder of this chapter is designed as follows: Section 13.2 discusses how the warranty service affects the overall revenue and the existing literature based on the same is also discussed. Section 13.3 gives the building blocks for modeling the sales function, and is followed by Section 13.4 which constitutes the modeling of all the cost components and profit function. In Section 13.5, the proposed model has been validated using a real-life data set. Section 13.6 discusses the managerial implications of this study and is followed by conclusion in Section 13.7

13.2 Role of warranty in determining overall profit: A literature review

Many researchers in the past have conducted studies to substantiate that effective warranty policies are an essential part for achieving the desired results. Careful warranty planning can lead to competitive success and at the same time a lack of attention toward it might result in huge losses which could have

been avoided by considering this very aspect. A warranty assures the customer that the product's stated promise will be delivered to them, which induces a sense of confidence in the customer at the time of purchase. Now, one may think that it would be beneficial for the manufacturer to lure buyers by providing a longer warranty period so as to give them better assurance against the prospect that a defect arises. However, since the warranty is an additional service, it would also incur some additional cost to the manufacturer which would eventually result in a higher asking price. Therefore there arises a need to maintain a balance between the offered warranty period and the price of the product.

Until now, the literature that has studied the effect of various warranty policies on management decisions has been well explored. [Nguyen et al. \(1988\)](#) modeled a framework to achieve the optimal profit by considering the implications of warranty costs. The warranty cost of second-hand products has been modeled by [Chattopadhyay et al. \(2001\)](#). Different warranty policies such as renewing and nonrenewing warranties have been discussed by [Murthy and Djameludin \(2002\)](#) to serve many purposes for both the manufacturer and the buyer. [Ladnay and Shore \(2004\)](#) formulated an optimal warranty period problem by the manufacturer's upper specification and lower specification limit of warranty. [Kapur et al. \(2014\)](#) studied the effect of warranty cost on overall profit that arises due to the deviation between product performance (PP) and customer expectations. Another study by [Aggrawal et al. \(2014\)](#) presented a methodology to obtain the optimal price and warranty length by considering the loss in revenue due to warranty cost. [Kapur et al. \(2015\)](#) incorporated an indirect warranty cost that occurs due to dissatisfaction of the customer in order to determine its effect on overall profit.

13.3 Formulation of sales function

To determine the sales cycle of an innovation, diffusion research has proved to be the only modeling framework in the field of marketing since the 1960s. The most significant and widely used model is that of Frank Bass, popularly known as the Bass model. The Bass model provides us with the framework to understand how a new product's current adopters interact with potential adopters. It classifies the adopters into innovators and imitators depending upon the degree of responsiveness after the information about a new innovation reaches them. However, the Bass model has taken only one factor into consideration which is the "time path," excluding any other marketing dimensions. However, in today's marketing scenario, the sales rate depends not only on time—the price also plays a vital role in governing the rate of adoption. Therefore, in the proposed problem, we have tried to combine both adoption time and price of the product to formulate a two-dimensional diffusion innovation model which was originally proposed by [Kapur et al. \(2010\)](#).

x is considered as the value of the product which is a function of continuation time, t ; revenue per unit, r_s and the output elasticity, α . Using the structure of [Cobb Douglas function \(1928\)](#) it is formulated as:

$$x(t, r_s) = t^\alpha \times r_s^{1-\alpha} \quad (13.1)$$

Therefore the two-dimensional model that is considered in this chapter is represented by the following differential equation:

$$n(x) = \frac{dN(x)}{dx} = p(m - N(x)) + \frac{q}{m} \times N(x)(m - N(x)) \quad (13.2)$$

where, $N(x)$ is the total number of adopters due to value of the product, x ; m is the potential market size; and p and q are the coefficients of external and internal influence, respectively.

Incorporating the initial condition $x(0, 0) = 0$, $N(0, 0) = 0$ and solving [Eq. \(13.2\)](#), we get:

$$N(t, r_s) = m \times \left[\frac{1 - e^{-(p+q)t^\alpha \times r_s^{1-\alpha}}}{1 + \frac{q}{p} e^{-(p+q)t^\alpha \times r_s^{1-\alpha}}} \right]$$

13.4 Optimization problem formulation

Industry 4.0 offers the opportunity for manufacturers to optimize their operations quickly and efficiently by knowing what needs attention. However, despite the fact that we have moved on to the Industry 4.0 era, there are certain aspects that are still governed by the philosophies given and channelized as far as Industry 3.0 is concerned. It is a fact that the overall profit of an industry, whether pertaining to 2.0, 3.0 or 4.0, will be affected by the resources spent by on the betterment of the product and various cost components that are associated at each stage of that process. Expenses such as production cost, research and development cost, and unreliability cost constitute the manufacturing cost function that an industry has to incur before releasing its final offering. Once the product reaches the customer and its performance is not able to satiate the customer's aspiration level, only then does the warranty comes into the picture. In the following subsections, we model both of these major cost functions and henceforth formulate the profit function.

13.4.1 Manufacturing cost modeling

13.4.1.1 Model for quantity produced

To calculate the amount of quantity produced, we have assumed that it is reliant on the quality or reliability of the product ([Agarwal et al., 2015](#)). Considering q_0

to be the initial production, the expression for quantity produced at any particular time point t with price per unit as r_s is given as exponentially dependent on the reliability index, ν of the product with parameter q_1 :

$$Q(t, r_s) = q_0 + q_1 \times e^{\nu(t^\alpha \times r_s^{1-\alpha})} \quad (13.3)$$

13.4.1.2 Manufacturing cost

The manufacturing cost comprises three types of cost components, which are research and development cost (to ensure maximum reliability and improved quality), production cost, and the cost associated with the product's unreliability.

To obtain the desired level of quality and reliability that the customer seeks, an industry needs to spend an ample amount of resources, which as a result increases the research and development cost. Assuming that this cost depends on the reliability index of the product (Liu et al., 2006), it is modeled as:

$$c_1(\nu) = (a + b\nu^k) \quad (13.4)$$

where, a is the fixed cost, and ν is the reliability index; $a, b, k, \nu > 0$.

The production cost is dependent on the initial quantity and the quantity produced at a particular time. Taking the cost structure of production cost as given by Liu et al. (2006) we get:

$$c_2(t) = C_0 \left(\frac{q_0}{Q(t, r_s)} \right)^\mu \quad (13.5)$$

where, μ is a fixed parameter and C_0 is the cost. The third and final cost component is that of unreliability cost, which is given by $c_3\nu^{-1}$, where c_3 is a fixed parameter. Therefore per unit total manufacturing cost is given by:

$$c(t, \nu) = [c_1 + c_2 + c_3\nu^{-1}] \quad (13.6)$$

As we can see from Eq. (13.6), the total manufacturing cost is a function of time and reliability, which in turn is dependent on many factors such as the quantity produced and unreliability factor.

13.4.2 Warranty cost modeling

Despite the vast amount of research and studies carried out to present the maximum reliable product to the customer, some margin of error is always left which gives rise to a conflicting situation between the customer and producer—a situation where the product does not perform up to the expectations of the customer. It is then that the warranty is used by the customer. Industries thereby have to provide the warranty service in the case of such a scenario, and hence incur some additional cost, which in turn affects the overall profit function. Therefore we need to determine the structure of PP and customer expectation (CE) in order to

model the warranty cost distribution. A target value for PP must be decided by the producer which should lie within a certain interval, give or take some variation. Hence, it becomes necessary to consider some distribution to reflect PP. Furthermore, each customer is unique in his or her tastes and preferences, which are also subject to change over time. Therefore we cannot take a permanent expected value for CE. Hence it is essential to represent CE with some form of distribution too. In the following subsections of the chapter, we attempt to make use of some definitions as given by [Kapur et al. \(2014\)](#) so as to model PP, CE, and warranty cost framework (WCF).

13.4.2.1 Possible number of complaints

The possible number of complaints is the total number of complaints that are likely to be made when the deviation between PP and CE crosses a predetermined value. Naturally, a customer would desire the product to perform much better than his expectations. Therefore PP should be as greater than CE as possible. Whenever PP is less than CE, the customer will be dissatisfied and file a complaint. Let D^* be this deviation between PP and CE and we restrict this difference by a threshold value d^* . A warranty complaint will occur whenever D^* is less than d^* . Let the possible number of complaints be denoted by *poss_n*. [Table 13.1](#) examines the scenarios where the same customer who is trying similar products of different brands will file a complaint or not based on the performance of the products.

13.4.2.2 Warranty probability

Let T denote the total number of products and, if *poss_n* is the total possible number of complaints, then warranty probability can be defined as the ratio of the possible number of complaints to the total number of products. Mathematically, it can be written as:

$$W_p = \frac{\text{poss_n}}{T} \quad (13.7)$$

Table 13.1 Scenarios where warranty complaint will occur or not.

PP	CE	PP – CE	Whether $D^* = PP - CE < d^* = 0.5$	Whether warranty complaint occurs or not
6	3	3	No	No
5	3	2	No	No
4	3	1	No	No
3	3	0	Yes	Yes
2	3	– 1	Yes	Yes
1	3	– 2	Yes	Yes

13.4.2.3 Actual number of complaints

Of the potential number of complainers who could have lodged a complaint for every situation where PP is less than CE, only a few actually file a complaint. We take that number as the actual number of complaints which is denoted by act_n .

13.4.2.4 Complaint factor

The term complaint factor, denoted by ω , is then defined as the ratio of the actual number of complaints to the potential number of complaints. Mathematically, it is represented as:

$$\omega = \frac{act_n}{poss_n} \quad (13.8)$$

$$\text{Or } act_n = \omega \times poss_n \quad (13.9)$$

Substituting the value of $poss_n$ from Eq. (13.7) to Eq. (13.9), we get

$$act_n = \omega \times T \times W_p$$

13.4.3 Formulation of warranty probability in terms of product performance and customer expectation

CE and PP are assumed to be independent of each other. Therefore we can make use of normal distribution to represent the distribution functions of both of them, that is,

$$CE \sim N(\mu_{CE}, \sigma_{CE}^2)$$

$$PP \sim N(\mu_{PP}, \sigma_{PP}^2)$$

And as discussed in an earlier section, since D^* is the deviation between PP and CE, it can be represented mathematically as

$$D^* = PP - CE \quad (13.10)$$

Previously, we assumed d^* to be the restricted value for D^* , below which the customer will file a complaint. Therefore, in a scenario where $D^* < d^*$, the customer will be dissatisfied and claim the warranty policy by filing a complaint.

Now, since PP and CE are two normal varieties, their difference will also be normally distributed as:

$$D^* = PP - CE \sim N\{\mu_{PP} - \mu_{CE}, \sigma_{PP}^2 + \sigma_{CE}^2\} \quad (13.11)$$

And, the probability of D^* being less than d^* (a situation where a complaint will occur) will be

$$P(D^* \leq d^*) = P[Z \leq z] = \left(\Phi \left(\frac{d^* - (\mu_{PP} - \mu_{CE})}{\sqrt{\sigma_{PP}^2 + \sigma_{CE}^2}} \right) \right) \quad (13.12)$$

From the above equation, we can also calculate the probability of D^* being greater than d^* , which is the situation where the customer is satisfied and does not complain. This is given as

$$P(D^* > d^*) = 1 - \Phi\left(\frac{d^* - (\mu_{PP} - \mu_{CE})}{\sqrt{\sigma_{PP}^2 + \sigma_{CE}^2}}\right) \quad (13.13)$$

Let A denote the cost of repairing one unit and let us assume that it is directly proportional to the square of difference between D^* and its restricted value.

Then A will be given by

$$A = k_1(D^* - d^*)^2$$

where k_1 is the constant of proportionality.

Now, we can give the structure for WCF mathematically as

$$WCF = act_n.A = k_1(D^* - d^*)^2 \omega T \left(\Phi\left(\frac{d^* - (\mu_{PP} - \mu_{CE})}{\sqrt{\sigma_{PP}^2 + \sigma_{CE}^2}}\right) \right)$$

To find the warranty cost per unit, let us take the value of the total number of products, $T = 1$. Therefore the per unit warranty cost is given by

$$WCF = act_n.A = k_1(D^* - d^*)^2 \omega \left(\Phi\left(\frac{d^* - (\mu_{PP} - \mu_{CE})}{\sqrt{\sigma_{PP}^2 + \sigma_{CE}^2}}\right) \right)$$

The above equation gives us the expression for warranty cost function for one unit.

Therefore the total cost component is the sum of the manufacturing cost and warranty cost component, that is,

$$(c(t, \nu).Q(t, r_s) + WCF.(N(t, r_s)))$$

13.4.4 Problem formulation for optimal profit

As we know that the total profit earned by any industry is calculated as the difference between the total revenue earned and all the costs incurred, so

Total Profit = Revenue – Cost

The cost also includes some implicit cost components which we have already discussed in the above sections. So after incorporating those costs, the above equation becomes:

Profit = Revenue – (Manufacturing Cost + Warranty Cost)

Therefore the net profit function, φ , can be written mathematically as: $\varphi(N(t, r_s)) = r_s \times N(t, r_s) - (c(t, \nu) \times Q(t, r_s) + WCF \times (N(t, r_s)))$.

Now, we substitute the expressions for $c(t, \nu)$ and WCF in the above equation and formulate our final optimization problem which aims at maximizing the net profit under the budget constraint C_B . This is presented as follows:

$$\begin{aligned} \text{Max } \varphi(N(t, r_s)) &= r_s \times N(t, r_s) \\ &- \left[(a + b\nu^k) + C_0 \left(\frac{q_0}{Q(t, r_s)} \right)^\mu + c_3\nu^{-1} \right] \times Q(t, r_s) \\ &- \left[k_1(D^* - d^*)^2 \times \omega \times \left(\Phi \left(\frac{d^* - (\mu_{PP} - \mu_{CE})}{\sqrt{\sigma_{PP}^2 + \sigma_{CE}^2}} \right) \right) \right] \times N(t, r_s) \quad (13.14) \end{aligned}$$

subject to

$$c(t, \nu) \times Q(t, r_s) + WCF \times N(t, r_s) \leq C_B$$

In the objective function given above, the first term represents the revenue that will be generated from the sale of $N(t, r_s)$ products. The second term constitutes the total cost incurred before the release of the $Q(t, r_s)$ products, that is, R&D, production, and unreliability costs. The third term is the WCF.

13.5 Numerical illustration

Sales data of 4K, DRAM (2014) have been used to estimate the parameters of the sales function. The values obtained are: $p = 0.003$, $q = 0.994$, $m = 315.679$, and $\alpha = 0.6$. The assumed parameters in the problem are listed in Table 13.2.

A budget of $C_B = 900$ has been considered to analyze the proposed model. Using LINGO software, we first calculated the optimal solution of problem (13.14) excluding the warranty cost component which gave us a profit of 975.06. After including the warranty cost component, the optimal solution of (13.14) was obtained as 2345.54.

13.6 Managerial implications

It has become evident that giving an additional service of warranty actually increases the overall profit. Providing service of warranty seems like a costly concern in the short run but it has proved to be an essential tool in keeping with the desired aspiration level of the customer in the long run. As shown in this chapter, the cost associated with the warranty claims can be reduced by focusing on enhancing the product's performance which will cover the deviation that arises

Table 13.2 Parameters used in the given problem.

Parameters	a	b	ν	k	C_0	c_3	q_0	q_1	d^*	k_1	ω	r_s	μ
Values	7	5	0.704	0.8	3	1	8	2	0.5	0.0592	0.05	39	0.4

between PP and CE. A customer has every right to assume that his expectations from the service in which he is investing will be met. However, if the organization fails to meet their expectations, it directly or indirectly affects both its reputation and revenue.

13.7 Conclusions

In the existing competitive and ever-growing market, change and adaptation are major factors that have helped all industries (2.0, 3.0, or, for now, 4.0) to maintain a balance between being profit oriented and customer oriented. This study considers both of these concepts to come up with a framework for an appropriate allotment of resources which not only helps any industry to attain higher profit but also aims at satiating the customer's aspiration level. The two major reasons that the CE level is violated are faulty engineering and mistreatment of customers. In both cases, it is the responsibility of industrial professionals to eradicate the factors that create such a conflicting situation. In the case of complaints, the warranty acts as a catalyst which not only helps in restoration of the lost faith in any industry but is also a great promotional tool. Focus should be laid on both aspects—engineering (infusion) and promoting (diffusion) in order to achieve higher sales and growth.

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Application of AHP in evaluating the financial performance of industries

14

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14.1 Introduction

India is recognized as one of the most rapidly growing economies, fueled by the persistent efforts across its society. Today, financial literacy has emerged as one of the exponential factors for the growth of the economy. With the increase in financial literacy, investors are now more concerned about all aspects of their investments. As the financial markets are volatile in nature, it is vital that investors adopt various strategies for investing. Investors ought to understand financial performance. For this, fundamental analysis is one of the methods used by investors to identify industries with good prospects and which tend to be fundamentally strong.

On the other hand, in this highly competitive and turbulent business environment, it is also profoundly important for industries to evaluate their financial

performance to hold a position in the market at large. Financial performance illustrates industries' ability to direct and control their resources to achieve their immediate business goals and also their future goals. A firm's performance is an imperative constituent because it characterizes the business value as the process of measuring the firm's operational proficiency and viability (Neely et al., 1995). Financial performance deals with the assessment and elucidation of a company's financial position and activities, and hence incorporates a comparison and annotation of accounting data (Eljelly, 2004). The rationale for financial analysis is to accumulate the information contained in the financial statements to facilitate judgment of the financial status of a company (Khan and Jain, 2005). Assessment of firm performance via financial ratios has been a conventional yet potent tool for all decision-makers, including financial managers, creditors, investors, business analysts, and others. Adopting these financial ratios, comparison can be made within a firm itself, with other companies, or among industries (Shaverdi et al., 2014). Investors and customers extract valuable quantitative financial information by assessing financial ratios. With the proper assessment of financial indicators, industries can be evaluated over time and even compared with other sectors. For achieving these objectives it is necessary for an industry to design a comprehensive and useful model for evaluating financial performance. For evaluating financial performance, various ratios are classified into clusters, such as liquidity, financial leverage, profitability, growth, and efficiency. Thus, this is a situation where management has multiple criteria for evaluating performance.

In this chapter, we apply a mathematical model which deals with multiple criteria, known as multicriteria decision-making (MCDM). An AHP model of MCDM has been used for the evaluation of the financial performance of Indian industry, and identifies the best indicator for evaluating performance. For the said purpose; first, by consideration of a literature review, various financial ratios have been extracted. Second, the hierarchical structure was framed for performance evaluation. Third, questionnaires were issued to financial academicians, financial experts, and financial researchers; finally, using the AHP model, the final value of global weights and ranking were determined.

14.2 Financial ratios

A ratio, necessarily, is an evaluation of two quantities demonstrating the estimation of one financial variable in comparison with another, and shows the firm's activities. It is viewed that decision-makers use these ratios for examining the relevant data to obtain meaningful information (Li, 2012).

Matsumoto et al. (1995) directed a survey of security analysts to substantiate their approach to financial ratios. They discovered that growth indicators were viewed as the most essential, followed by valuation, and then profitability indicators (Altman, 1968). Beaver (1966) demonstrated that these ratios were utilized to create models to foresee financial distress or failures. They proposed that

financial indicators were also used to predict expected performance. [Schumacher and Boland \(2003\)](#) analyzed the business performances of publicly traded and cooperatively owned food agribusiness firms. They used accounting profitability measures to assess the performance. They considered return on equity as an dependent variable to study the industry and corporate effects.

[Dharmaraj \(2013\)](#) studied the financial performance of automobile industries for the period of 1998–99 to 2011–12. In this study it was found that the automobile sector was financially viable and booming at 17% per annum. The outcomes suggested that the current ratio, fixed asset turnover ratio, and debt turnover ratio were significantly different. Meanwhile, inventory turnover ratio, debt equity ratio, return on net worth, and interest coverage ratio showed insignificant differences for the selected automobile companies.

[Paghadar \(2013\)](#) made a comparative analysis of the steel industry in India for the 5 years from 2009–10 to 2013–14. Liquidity ratios, solvency ratios, and profitability ratios were used to evaluate the financial performance. The study noted that the net profit and inventory management of Tata Steel Ltd. outperformed the other companies. [Borhan et al. \(2014\)](#) examined the impact of financial ratios on the financial performance of chemical companies. The liquidity, leverage, and profitability ratios were measured for the period from 2004 to 2011. The study revealed that the profitability ratios were the key factors which profoundly influence the financial performance, rather than liquidity and leverage ratios. [Katchova and Enlo \(2013\)](#) reviewed the financial performance of publicly traded agribusiness firms over the period 1961–2011. This study considered the profitability, liquidity, and market ratios to assess performance. The results observed that the return on equity was higher than the other parameters, indicating the working effectiveness of these agribusinesses.

14.2.1 Liquidity ratios

These ratios exhibit a firm's capacity to meet its commitments in the short term.

Current ratio indicates the proportion of current assets to the value of current liabilities. This ratio indicates a corporation's ability to meet its short-term liabilities from the value of current assets.

$$\text{Current ratio} = \frac{\text{Current assets}}{\text{Current liabilities}}$$

Quick ratio is the proportion of quick assets to the value of current liabilities. Quick assets are the most liquid assets, which generally can be computed by reducing the value of inventories from the sum of current assets. This ratio displays a business's ability to meet its short-term liabilities from the total of liquid assets.

$$\text{Quickratio} = \frac{\text{Current assets} - \text{Inventories}}{\text{Current liabilities}}$$

Cash ratio is the proportion of the absolute measure of cash and marketable securities of the company to the value of current liabilities. This ratio

appraises how much a corporation can quickly sell its assets and cover its entire value of current liabilities.

$$\text{Cashratio} = \frac{\text{Cash} + \text{Marketable securities}}{\text{Current liabilities}}$$

14.2.2 Financial leverage ratios

These indicators typify the commitment of an industry's fixed financing and its capacity to meet its fixed financing liabilities.

Debt ratio displays the level of the aggregate sum of assets being financed to the total amount of debt.

$$\text{Debt ratio} = \frac{\text{Total debt}}{\text{Total assets}}$$

Shareholders' equity to total assets ratio signifies the aggregate sum of assets being financed with the total amount of shareholder equity.

$$\text{Shareholders' equity to total assets ratio} = \frac{\text{Shareholders' equity}}{\text{Total assets}}$$

Fixed assets to shareholders' equity ratio indicates the proportion of the aggregate sum of fixed assets to the shareholder equity.

$$\text{Fixed assets to shareholders' equity ratio} = \frac{\text{Fixed assets}}{\text{Shareholders' equity}}$$

Fixed assets to long-term debt ratio indicates the proportion of the aggregate sum of fixed assets with the amount of long-term debt.

$$\text{Fixed assets to long-term debt ratio} = \frac{\text{Fixed assets}}{\text{Long-term debt}}$$

14.2.3 Profitability ratios

These ratios evaluate the overall efficacy of the company concerning revenue generated against expenses and other related costs.

Net profit margin ratio reveals the earnings after taxes to the net amount of sales.

$$\text{Net profit margin ratio} = \frac{\text{Earnings after taxes}}{\text{Sales}} \times 100$$

Return on equity ratio is expressed as a percentage of profits to the net worth of the company.

$$\text{Return on equity ratio} = \frac{\text{Net profit before taxes}}{\text{Net worth}} \times 100$$

Return on investment ratio is measured as a percentage of profits to the total investment of the company.

$$\text{Return on investment ratio} = \frac{\text{Net profit}}{\text{Total investment}} \times 100$$

14.2.4 Growth ratios

Growth ratios show a numerical measure of the augmentation or diminishment in the valuation of the company over a time frame.

Sales growth ratio demonstrates the expansion in the amount of sales for a company over a particular time frame.

$$\text{Sales growth ratio} = \frac{S_t - S_{t-1}}{S_{t-1}} \times 100$$

where S_t is sales of current period and S_{t-1} is sales of last period.

Operating profit growth ratio shows the level of increment in the amount of operating profit over a time frame.

$$\text{Operating profit growth ratio} = \frac{OP_t - OP_{t-1}}{OP_{t-1}} \times 100$$

where OP_t is operating profit of current period and OP_{t-1} is operating profit of previous period.

Shareholders' equity growth ratio illustrates the percentage of increment in shareholder equity between the two-time frame.

$$\text{Shareholder's equity growth ratio} = \frac{SE_t - SE_{t-1}}{SE_{t-1}} \times 100$$

where SE_t is shareholder's equity of current period and SE_{t-1} is shareholder's equity of previous period.

Assets growth ratio indicates the level of increment in the amount of assets over the time period.

$$\text{Assets growth ratio} = \frac{A_t - A_{t-1}}{A_{t-1}} \times 100$$

where A_t is assets of current period and A_{t-1} is assets of previous period.

The financial ratios as indicated by the considered approach are shown in Table 14.1.

14.3 Methodology

14.3.1 Multicriteria decision-making

Decision-making is an indispensable part of all business processes. It is the process through which decision-makers select the best alternative among all the

Table 14.1 Financial ratios used in the model

Category	Code	Ratio
Liquidity ratios (C1)	C11	Current ratio
	C12	Quick ratio
	C13	Cash ratio
Financial leverage ratios (C2)	C21	Debt ratio
	C22	Shareholders' equity to total assets ratio
	C23	Fixed assets to shareholders' equity ratio
	C24	Fixed assets to long-term debt ratio
Profitability ratios (C3)	C31	Net profit margin
	C32	Return on equity
	C33	Return on investment
Growth ratios (C4)	C41	Sales growth ratio
	C42	Operating profit growth ratio
	C43	Shareholders' equity growth ratio
	C44	Asset growth ratio

available alternatives. The difficulty arises for decision-makers with the presence of more than one criterion. For this, MCDM is the eminent part of the decision-making process. It is the subdivision of operational research (or OR) models which deals with the framework and solving problems including multicriteria. Typically it is crucial to use the preferences of decision-makers to differentiate between alternatives when a unique solution does not exist.

MCDM is a mathematical model under which decision problems are expressed in a matrix format. Let X be the $(M \times N)$ decision matrix under which component a_{ij} illustrates the relative importance of alternative A_i when it is assessed regarding decision criteria C_j , ($i = 1, 2, 3, \dots, M$, and $j = 1, 2, 3, \dots, N$). It is additionally presumed that the weights (denoted by W_j , for $j = 1, 2, 3, \dots, N$) of relative importance of the decision criteria have been computed by the decision-maker.

	<i>Criterion</i>			
	C1	C2	C3	CN
Alt.	W1	W2	W3	WN
A1	a11	a12	a13	a1N
A2	a21	a22	a23	a2N
A3	a31	a32	a33	a3N
aM	aM1	aM2	aM3	aMN

14.3.2 Analytical hierarchy process

In the 1980s, AHP was presented by Saaty and the methodology was utilized as an approach for MCDM. It is a problem-solving framework which has been

proposed to evaluate complex decision problems among one or more decision-makers. It is conceivable to unveil the choices of decision-makers and to infer their weights by way of AHP (Saaty, 1980; Gao and Hailu, 2012). It involves a multilevel hierarchical framework which is comprised of the objectives, criteria, subcriteria, and alternatives for solving decision problems. Li (2012) proposed a hierarchical structure of financial indicators to build an enterprise comprehensive evaluation index. Shaverdi et al. (2014) enforced a hierarchical framework for assessing the performance of the Iranian petrochemical industry.

The procedure of AHP is analyzed in the following steps.

Step 1: Identify criteria and alternatives:

The AHP procedure was initiated with the identification of criteria and subcriteria. First, the four criteria are liquidity indicators, financial leverage indicators, profitability indicators, and growth indicators. Subsequently, under liquidity indicators, there are three subcriteria: current ratio, quick ratio, and cash ratio. Then, the financial leverage indicators are comprised of four subcriteria: debt ratio, shareholders' equity to total assets ratio, fixed assets to shareholders' equity, and fixed assets to long-term debt ratio. For profitability indicators, there are three subcriteria, namely, net profit margin, return on equity, and return on investment. Finally, for growth indicators, the subcriteria are sales growth ratio, operating profit growth ratio, shareholders' equity growth ratio, and assets growth ratio. In this study we have developed a two-level AHP for evaluating financial performance, as shown in Fig. 14.1.

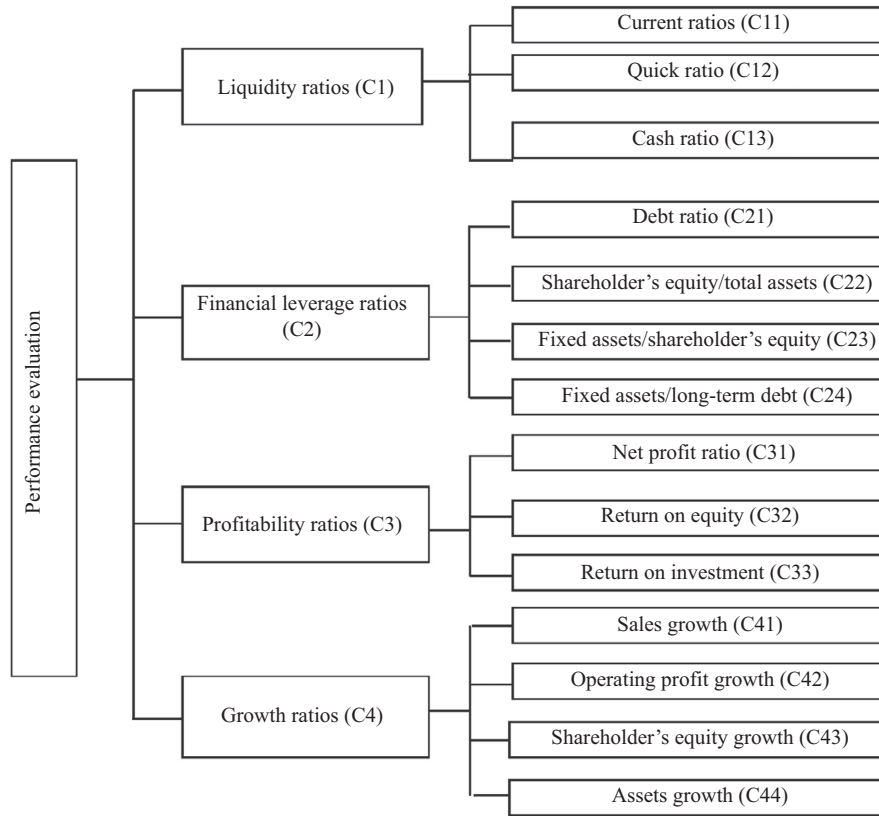
Step 2: AHP questionnaire:

The questionnaire was administered to respondents for measuring the financial performance. The foremost rationale of this study is to identify the relative weights of the criteria and subcriteria of financial performance. For this purpose, the questionnaire was structured by way of AHP, to scrutinize the significance between two criteria in a comparable level. The scale was bifurcated into ranks 1–9. The ranks on the left demonstrate that the criteria on the left were indispensable as compared to the right.

In contrast, the ranks on the right denoted that the criteria on the right were treated as more crucial than those on the left (Leung and Chin, 2004). The questionnaire was given to financial experts comprising financial researchers, financial academicians, and financial consultants. In total, there were 30 experts, 60% male and 40% female, all aged 25–45 years. All the respondents had a deep understanding of financial concepts, investments, and other financial matters.

Step 3: Develop a pairwise comparison decision matrix which pertinently demonstrates criteria weights:

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2n} \\ a_{31} & a_{32} & a_{33} & \cdots & a_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & a_{n3} & \cdots & a_{nn} \end{bmatrix}$$

**FIGURE 14.1**

The proposed hierarchical framework.

The various criteria are quantified by the decision-makers using the standard scale of pairwise comparison in [Table 14.2 \(Saaty and Vargas, 1991\)](#).

The component $aij(i, j = 1, 2, \dots, n)$ in the matrix shown and where a_{ij} is:

$$aij = \frac{1}{aji}, aii = 1, aij > 0.$$

Step 4: Group integration:

The approach of the geometric mean was utilized to integrate the experts' opinions, the formula is:

$$aij = (aij^1 \otimes aij^2 \otimes \dots \otimes aij^n)^{\frac{1}{n}}$$

Table 14.2 Scale of relative importance

Definition	Value
Equally important	1
Moderately important	3
Essentially important	5
Very strongly important	7
Extremely important	9
Intermediate values	2, 4, 6, 8

Step 5: Normalize the decision matrix:

Now, the mathematical procedure embarks on finding and normalizing the criteria weights. The formula is as follows:

$$\overline{a_{ij}} = \frac{a_{ij}}{\sum_{i=1}^n a_{ij}}$$

where n is number of criteria; a_{ij} is comparison value by contrasting factor i with factor j ; $\sum_{i=1}^n a_{ij}$ is summing of the comparison value; $\overline{a_{ij}}$ is normalized comparison value.

Step 6: Calculate the weights:

Weights of the matrices are calculated by averaging each row. This step creates the criteria weight matrix W^T .

Step 7: Determine the eigenvalue of matrix X :

This is computed as follows:

- Multiply matrix X and the matrix of criteria weight W^T to get XW^T .
- Calculate lambda max ($\lambda_{\max}$) for computing consistency index (CI).

Note: $\lambda_{\max}$ is the highest eigenvalue (also referred to as principal eigenvalue) and calculated by multiplying AW^T with the sum of each column of the matrix X .

Step 8: Compute the CI (consistency index) and CR (consistency ratio):

This is computed as follows:

Step 8.1: Determine the CI using the following formula:

$$CI = \frac{\lambda_{\max} - n}{n - 1}$$

Step 8.2: Use the following formula to determine the CR:

$$CR = \frac{CI}{RI}$$

Inferences drawn from the AHP method are viewed as inconsistent when the CR value is higher than 0.1. All things considered, the decision-makers will be approached to reassess their decisions until adequate consistency is accomplished (Table 14.3).

Table 14.3 Random index (RI) (Saaty, 1980)

<i>n</i>	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Table 14.4 Normalized weights of main criteria (financial indicators)

Criteria	C1	C2	C3	C4	Geometric mean of the row (v_j)	Normalized weights (w_j)
C1	1	0.9287	0.3474	0.6146	0.6673	0.1567
C2	1.0767	1	0.5747	1.7234	1.0162	0.2386
C3	2.8785	1.7402	1	1.5304	1.6640	0.3907
C4	1.8180	0.5802	0.6534	1	0.9112	0.2140
Sum					4.2586	1

$$\lambda_{\max} = 4.1350, CI = 0.0450, RI = 0.90, CR = 0.05$$

where n corresponds to the number of criteria, and random index (RI) is the average consistency index generated randomly for making a pairwise comparison.

14.4 Experiments and results

To calculate the survey results, the judgment matrices were pairwise analyzed. The priority weights of all the fundamental criteria and subcriteria were first computed and then joined with all progressive hierarchical levels in each matrix to discover the global weights. The higher the mean value of the global weight, the more prominent the relative significance. This helps to extricate the more substantial elements from the less significant ones.

14.4.1 Data analysis

Table 14.4 exhibits the weights of various criteria for evaluating financial performance, based on the experts' opinions. The results and data analysis are discussed below.

14.4.1.1 Criteria level

The results for the criteria level in Table 14.4 indicate that the key performance indicators in evaluating financial performance are profitability indicators (C3) with a priority vector of 0.3907, and then financial leverage (C2) with a weight of 0.2386, growth indicators (C4) with a weight of 0.2140, and liquidity indicators (C1) with a priority vector of 0.1567. Therefore the profitability indicators are the

Table 14.5 Normalized weights of subcriteria (liquidity position indicators)

Subcriteria	C11	C12	C13	Geometric mean of the row (v_j)	Normalized weights (w_j)
C11	1	0.5869	0.9035	0.8094	0.2600
C12	1.7037	1	1.8028	1.4536	0.4670
C13	1.1068	0.5547	1	0.8499	0.2730
Sum				3.1129	1

$\lambda_{\max} = 3.0027$, CI = 0.0014, RI = 0.58, CR = 0.0024

Table 14.6 Normalized weights of subcriteria (financial leverage Indicators)

Subcriteria	C21	C22	C23	C24	Geometric mean of the row (v_j)	Normalized weights (w_j)
C21	1	1.5306	2.7604	0.9190	1.4038	0.3296
C22	0.6533	1	1.2854	0.5348	0.8187	0.1922
C23	0.3623	0.7780	1	0.4900	0.6096	0.1431
C24	1.0881	1.8697	2.0408	1	1.4275	0.3351
Sum					4.2595	1

$\lambda_{\max} = 4.0190$, CI = 0.0063, RI = 0.90, CR = 0.007

most critical indicators for industries to evaluate their financial performance. The consistency ratio is $0.05 < 0.1$, since the CR is less than 0.1, which demonstrates that the decision matrix is consistent. Thus, the decision-makers should concentrate on the profitability indicators such as net profit ratio, return on equity, and return on investment.

14.4.1.2 Subcriteria level

In the hierarchical framework, the second level is comprised of subcriteria for the main criteria, namely, liquidity, financial leverage, profitability, and growth indicators.

The result concerning the liquidity indicators as given in Table 14.5 shows that the priority of subcriteria was quick ratio (0.4670), followed by cash ratio (0.2730), and finally current ratio (0.2600). The consistency ratio is $0.0024 < 0.1$, which demonstrates that the decision matrix is consistent.

Turning to the financial leverage criteria, Table 14.6 illustrates that the most critical subcriterion is fixed assets/long-term debt (0.3351), followed by debt ratio (0.3296), then shareholders' equity/total assets (0.1922), and finally fixed assets/

Table 14.7 Normalized weights of subcriteria (probability indicators)

Subcriteria	C31	C32	C33	Geometric mean of the row (v_j)	Normalized weights (w_j)
C31	1.0000	0.5756	0.4618	0.6429	0.2047
C32	1.7374	1.0000	0.9613	1.1865	0.3778
C33	2.1654	1.0403	1.0000	1.3109	0.4174
Sum				3.1403	1

$$\lambda_{\max} = 3.0036, CI = 0.0018, RI = 0.58, CR = 0.0031$$

Table 14.8 Normalized weights of subcriteria (growth indicators)

Subcriteria	C41	C42	C43	C44	Geometric mean of the row (v_j)	Normalized weights (w_j)
C41	1	0.4616	0.3707	0.8257	0.6131	0.1441
C42	2.1665	1	0.7291	1.7652	1.2922	0.3037
C43	2.6974	1.3716	1	1.4359	1.5182	0.3568
C44	1.2110	0.5665	0.6964	1	0.8314	0.1954
Sum					4.2549	1

$$\lambda_{\max} = 4.0298, CI = 0.0099, RI = 0.90, CR = 0.0110$$

shareholders' equity (0.1431). The consistency ratio is $0.007 < 0.1$, which validates that the decision matrix is consistent.

This results in showing that the fixed assets/long-term debt would primarily affect the financial performance in the context of financial leverage indicators.

Table 14.7 illustrates that, for profitability indicators, the ranking of the subcriteria is: return on investment (0.4174), then return on equity (0.3778), and finally net profit ratio (0.2047). The decision matrix is consistent as the consistency ratio is 0.0031, which is below the limit of 0.1.

Table 14.8 demonstrates that, for the growth indicators, the most important subcriteria were shareholders' equity growth (0.3568), followed by operating profit growth (0.3037), then assets growth (0.1954), and finally sales growth (0.1441). The consistency ratio is $0.011 < 0.1$, which validates that the decision matrix is consistent.

Table 14.9 demonstrates the global weights of the subcriteria for evaluating financial performance. As per these results, the most important criterion was return on investment with global weight of 0.1630, followed by return on equity (0.1476), and finally the least important criterion was fixed assets to shareholders' equity (0.0341).

Table 14.9 Global weights and ranking

No.	Criterion	Weight (E)	Subcriterion	Weight (F)	Global weights of subcriteria (G)	Ranking
1	C1	0.1567	C11	0.2600	0.040742	12
			C12	0.4670	0.0731789	7
			C13	0.2730	0.0427791	10
2	C2	0.2386	C21	0.3296	0.07864256	5
			C22	0.1922	0.04585892	9
			C23	0.1431	0.03414366	13
			C24	0.3351	0.07995486	4
3	C3	0.3907	C31	0.2047	0.07997629	3
			C32	0.3778	0.14760646	2
			C33	0.4174	0.16307818	1
4	C4	0.2140	C41	0.1441	0.0308374	14
			C42	0.3037	0.0649918	8
			C43	0.3568	0.0763552	6
			C44	0.1954	0.0418156	11

E, Criteria weights; F, subcriteria weights; G, global weights ($E \times F$).

14.5 Discussion and conclusions

The share price of any company itself is clear enough to give an indication of the position of the company in the industry. Although many factors have an effect on the share price, undoubtedly financial performance has a major input. Financial performance is one of the potent tools which deal with meeting the financial objectives of industries. Hence, its analysis is something that cannot be neglected, either by stakeholders nor the industry itself. By using a more concrete, optimal, and most importantly, a mathematical model, industry and stakeholders can assess the most preferred ratio influencing their decision-making. In doing so, the AHP mathematical model was used to evaluate overall financial performance. The identified global ranking of the financial indicators provides an insight for the stakeholders to judge the fundamental versatility of the industry within a particular market. This study fundamentally emphasizes the financial indicators utilized for evaluating financial performance of industries.

With this aim, a comprehensive approach was adopted for evaluating financial performance. In this chapter, we have examined the key financial indicators by using the AHP method. A total of four criteria and 14 subcriteria have been scrutinized through expert opinions. An AHP approach then was used to integrate the expert opinions to obtain the key financial indicators for gauging the financial performance of industries. Finally, global weights and ranking of financial ratios were identified. With this model, investors and other stakeholders will be able to make comparative financial analysis for rational decision-making.

The proposed framework will help industries to carry out self-assessment and be able to illustrate their position in the market. This model has shown the preferences of financial experts, academicians, consultants, and others regarding the assessment of financial performance. This study found that the profitability indicators (subcriterion, return on investment) were preferred over the other financial indicators. This indicates that profitability is something that should not be overlooked and should be taken seriously. Above all, profitability position decisions must be made by the industry.

The indicators undertaken for this study are the most prevalent sources of assessing financial performance in almost every industry. Thus, the same can be used to find the best indicators for a particular industry. However, some additional ratios can also be considered, subject to the usage and importance they hold in evaluating the performance of any individual industry, for instance, the banking industry. Conclusively, indicators relevant to a particular industry can be used as input to arrive at the best indicator using the proposed model. Thus, this proposed model can be enhanced if such considerations are to be taken into account for evaluating financial performance.

For future studies, applying different techniques, such as FUZZY AHP, PROMETHEE, TOPSIS, VIKOR, and others, is suggested. This study has utilized quantitative financial indicators, and future research could apply both qualitative and quantitative ratios. Additionally, the application and creation of this model in specific industries could be another recommendation for exploiting this model further.

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Application of Internet of Things-aided simulation and digital twin technology in smart manufacturing

15

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15.1 Introduction

Technological growth and evolution have been the driving forces of manufacturing for centuries. The First Industrial Revolution occurred in the 1800s with the mechanization of production utilizing steam power. The Second Industrial Revolution occurred in the early 1900s when the first electrically powered assembly lines introduced mass production. The Third Industrial Revolution began in

the late 1960s when automation became possible by utilizing programmable logic controllers (PLCs), IT systems, and robotics. Now, in the early 2000s, manufacturing systems find themselves amid Industry 4.0: the integration of autonomous decision-making, machine learning, and Big Data analysis to create a smart factory with interoperability through the Internet of Things (IoT) and cloud computing. The development of information technologies and artificial intelligence technologies has resulted in new-generation intelligent manufacturing systems (Brettel et al., 2014; Bilberg and Malik, 2019; Elahi, 2016; Franchetti et al., 2016a).

This chapter is organized as follows. Section 15.2 and its subsections describe the general application of Industry 4.0 in smart manufacturing systems. Section 15.3 and its subsection elaborate on digital twin-driven smart manufacturing and introduce a reference model for that. Section 15.4 mainly focuses on the required stages for creating of a digital twin in smart manufacturing systems. Finally, a summary of this chapter is presented in Section 15.5.

15.2 Smart manufacturing systems and Industry 4.0 technologies—a glimpse

A smart manufacturing system represents a leap forward from more traditional automation to a fully connected and flexible system. A system that can utilize a constant stream of data from connected operations and production systems to learn and adapt to new demands. In other words, it is a flexible system that can self-optimize performance across a broader network, self-adapt to and learn from new situations in real or near-real time, and autonomously run entire production and operation processes (Elahi et al., 2020). Fig. 15.1 portrays a smart manufacturing system and its main features including (1) connectivity, (2) optimization, (3) transparency, (4) proactivity, and (5) agility. Fig. 15.2 shows a schematic view of those main features in a smart manufacturing system.

Industry 4.0 encompasses the promise of a new industrial revolution. A revolution that marries advanced manufacturing techniques with the IoT to create manufacturing systems that are not only interconnected, but communicate, analyze, and use information to drive further intelligent action back in the physical world. It connects physical with digital, and allows for better collaboration and access across departments, partners, vendors, product, and people. Industry 4.0 empowers manufacturing systems to better control and understand every aspect of their operation, and allows them to leverage instant data to boost productivity, improve processes, and drive growth (Din, 2018; Elahi and Wooten, 2019; Ottah and Elahi, 2019; Elahi and Leeth, 2019). A major element of Industry 4.0 is the cyberphysical system, a platform in a sensor-enabled smart work environment for managing networks of interacting elements between computational and physical components (Thoben et al., 2017; Elahi and Franchetti, 2015a; Elahi, 2016).

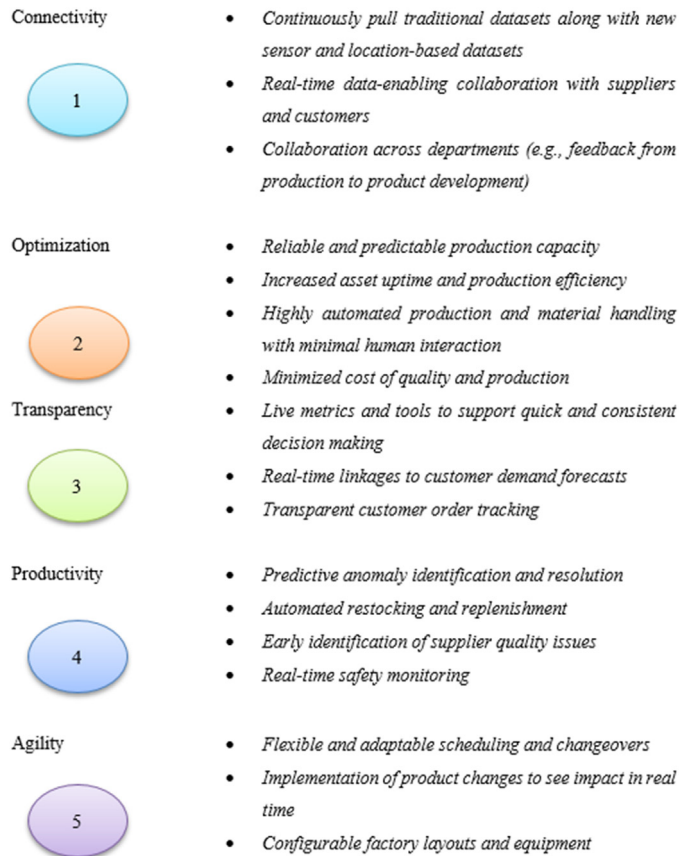


FIGURE 15.1 Main features of a smart manufacturing system (Deloitte University Press, 2017).

15.2.1 Autonomous mobile robots

An essential component of Industry 4.0 is autonomous production methods powered by the IoT concept. The idea that by harnessing a connected mesh of objects, devices, and computers, machines can communicate with each other. Autonomous robots are an influential example across countless industries, including manufacturing. By connecting to a central server, database, or PLC, the actions of robots can be coordinated and automated to a greater extent than ever before. They can complete tasks intelligently, in an orchestrated manner with minimal human input. Materials can be transported across the factory floor via autonomous mobile robots, avoiding obstacles, coordinating with fleet mates, and identifying where pickups and drop-offs are needed in real time (Figs.15.3–15.5).

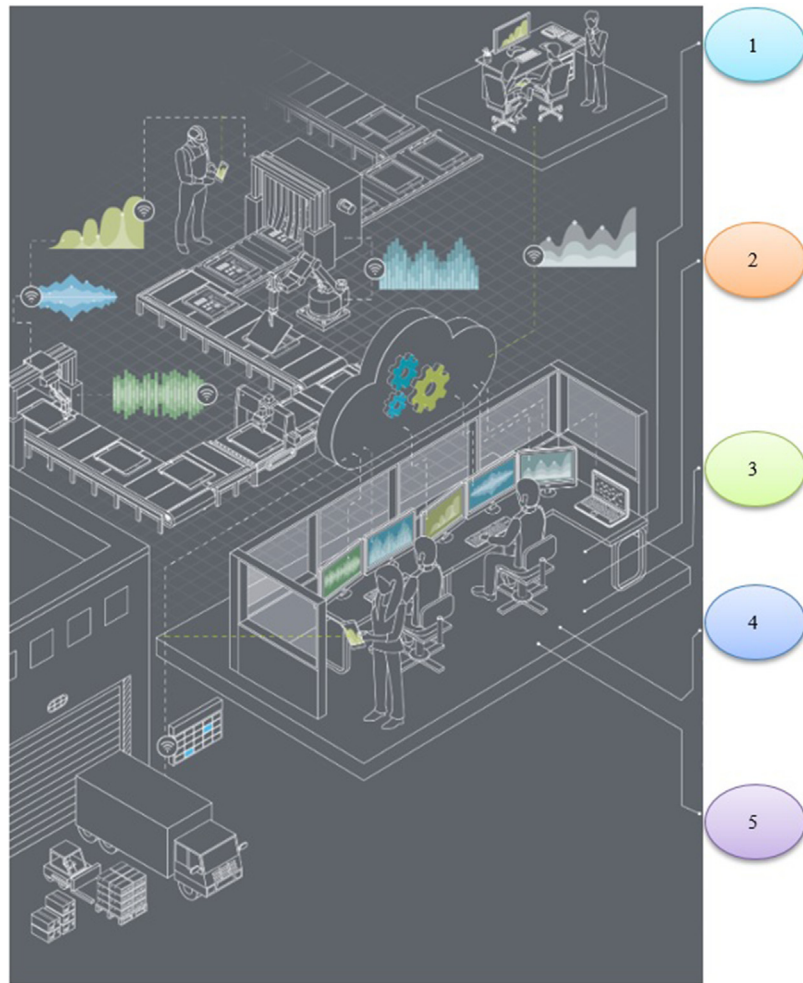


FIGURE 15.2 Schematic View of Main features in a Smart Manufacturing System (Deloitte university press, 2017).

15.2.2 The industrial Internet of Things

There were forecast to be around 30 billion devices connected to the Internet by 2020 (see Fig.15.6; Statista, 2019). While the promise of the IoT brings many new business prospects, it also presents significant challenges ranging from technology architectural choices to security and privacy concerns (Elahi and Franchetti, 2014; Elahi and Franchetti, 2013). To better follow this technical trend, industries should prepare themselves for these challenges. The IoT is “A network of items—each embedded with sensors—which are connected to the

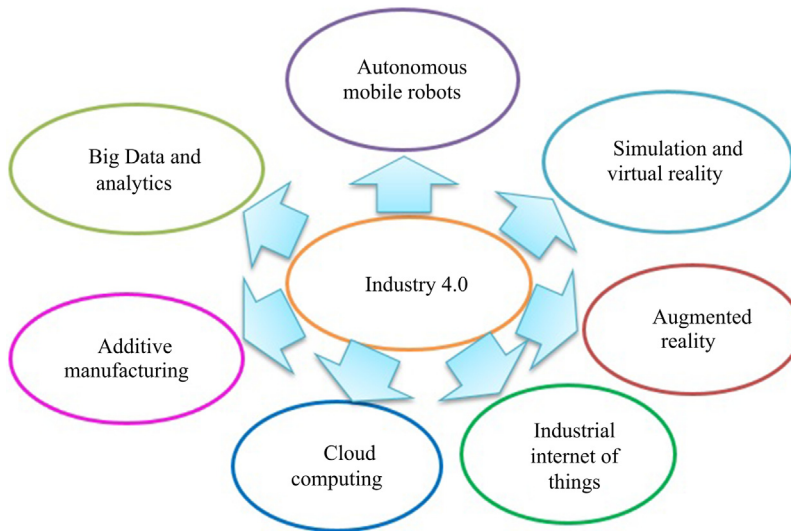


FIGURE 15.3 Industry 4.0 technologies.

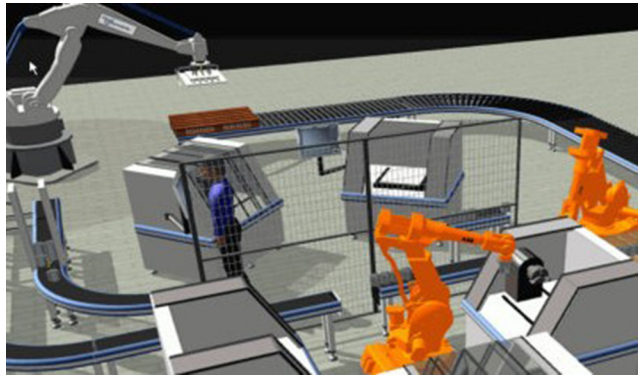


FIGURE 15.4 An automated manufacturing cell created in SIMIO Version 9.147 software environment.

Internet.” Its true value lies in the data that interconnected items share. The IoT has added a new term to the lexicon: “business intelligence.” For example, in a smart water resource management system, when the sensor detects that the water levels in a tank are too low, the system will call you and allow you to remotely refill the tank from a reservoir. The industrial IoT (IIoT) is “the use of smart sensors and actuators to enhance manufacturing and industrial processes.” The IIoT leverages the power of smart machines and real-time analytics. Connected sensors

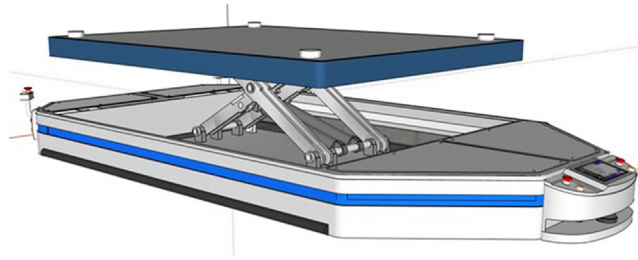


FIGURE 15.5 An example of an automated guided vehicle for material handling in a smart manufacturing system.



FIGURE 15.6 Internet of Things (IoT)-connected devices installed base worldwide from 2015 to 2025 (in billions).

and actuators enable companies to pick up on inefficiencies and problems sooner, and save time and money in addition to supporting business intelligence efforts. In manufacturing specifically, the IIoT holds great potential for quality control, sustainable and green practices, supply chain traceability, and overall supply chain efficiency. In an industrial setting, the IIoT is key to processes such as predictive maintenance, enhanced field service, energy management, and asset tracking (Fig. 15.7).

15.2.3 Additive manufacturing

Due to the IIoT, the prerequisites for production and manufacturing electronics are undergoing fundamental change. The “smart factory” is just around the corner: in the future, production facilities and value chains will be connected to one

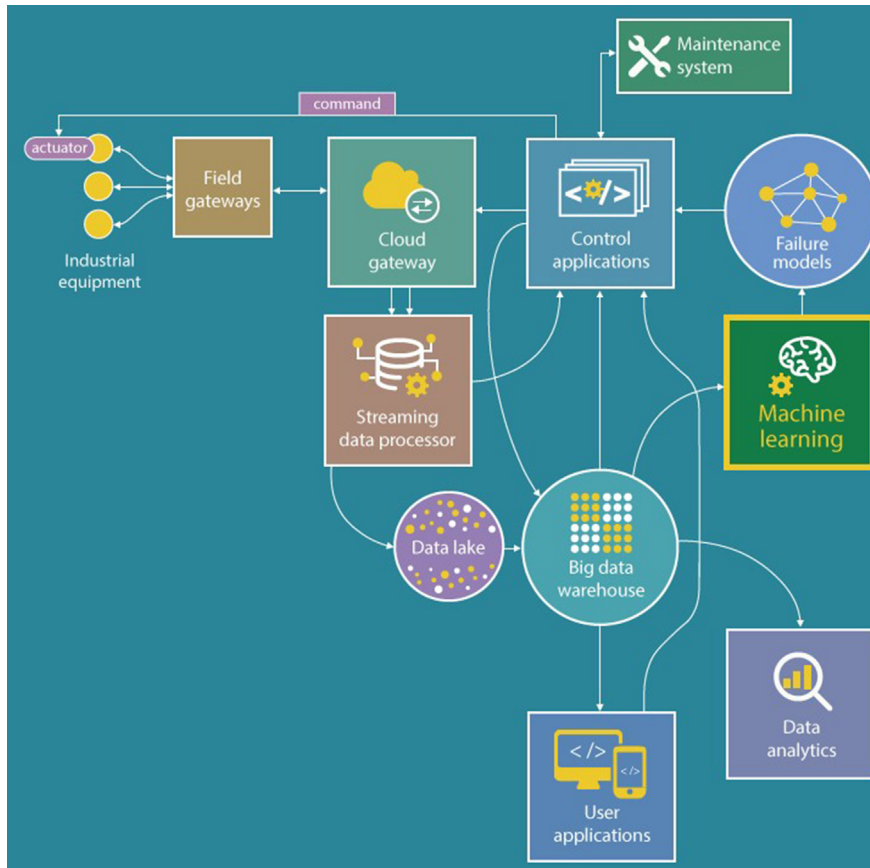


FIGURE 15.7 IoT-based predictive maintenance architecture in a smart manufacturing system (Science Soft, 2019).

another digitally. This poses some considerable challenges to companies: How can they prepare for this development? What opportunities and what risks are associated with this development? How can intelligent production planning further optimize the utilization rate of manufacturing facilities? What is important when it comes to the infrastructure and security of industrial IT? How can existing systems be adapted for modern cloud, mobility, and analysis functions? Additive manufacturing (AM), also known as 3D printing, is a “transformative approach to industrial production that enables the creation of lighter, stronger parts and systems.” It is defined as the process of joining materials to make objects from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing methodologies (Elahi, et al., 2011a; Elahi et al., 2011b). The primary applications of additive fabrication are design/modeling, fit and function

prototyping, and direct part production (Edgar and Tint, 2015; Franchetti et al., 2016b, 2017; Elahi et al., 2011c; Elahi et al., 2011d).

15.2.3.1 Additive manufacturing processes

There are a number of distinct AM processes with their own standards, which include (1) binder jetting, (2) directed energy deposition, (3) material extrusion, (4) powder bed fusion, (5) sheet lamination, (6) vat polymerization, and (7) wire arc AM.

Binder jetting uses a 3D printing style head moving on x, y, and z axes to deposit alternating layers of powdered material and a liquid binder as an adhesive.

Direct energy deposition AM can be used with a wide variety of materials including ceramics, metals, and polymers. A laser, electric arc, or electron beam gun mounted on an arm moves horizontally melting wire, filament feedstock, or powder to build up material as a bed moves vertically.

Material extrusion is a common AM process which uses spooled polymers which are either extruded or drawn through a heated nozzle which is mounted on a movable arm. This builds melted material layer by layer as the nozzle moves horizontally and the bed moves vertically. The layers adhere through temperature control or chemical bonding agents.

Powder bed fusion is the fastest growing metal AM segment currently. Powder bed fusion with metals is already making significant contributions to the aerospace, automotive, healthcare, and oil and gas industries. Powder bed fusion encompasses a variety of AM techniques including direct metal laser melting, direct metal laser sintering, electron beam melting, selective laser sintering, and selective heat sintering. Electron beams, lasers, or thermal print heads are used to melt or partially melt fine layers of material after which excess powder is blasted away.

Sheet lamination can be split into two technologies; laminated object manufacturing and ultrasonic AM. Laminated object manufacturing is suited to creating items with visual or aesthetic appeal and uses alternate layers of paper and adhesive. Ultrasonic AM uses ultrasonic welding to join thin metal sheets; a low-energy, low-temperature process, it can be used with various metals such as aluminum, stainless steel, and titanium.

Vat polymerization uses a vat of liquid resin photopolymer to create an object layer by layer. Mirrors are used to direct ultraviolet light which cures each resin layer through photo-polymerization.

Wire arc AM uses arc welding power sources and manipulators to build 3D shapes through arc deposition. This process commonly uses wire as a material source and follows a predetermined path to create the desired shape. This method of additive manufacture is usually performed using robotic welding equipment.

15.2.3.2 Additive manufacturing technologies

AM technologies can be broadly divided into three types. The first of which is sintering, whereby the material is heated without being liquefied to create complex high-

resolution objects. Direct metal laser sintering uses metal powder, whereas selective laser sintering uses a laser on thermoplastic powders so that the particles stick together. The second AM technology fully melts the materials, this includes direct laser metal sintering which uses a laser to melt layers of metal powder, and electron beam melting, which uses electron beams to melt the powders. The third broad type of technology is stereolithography, which uses a process called photo-polymerization, whereby an ultraviolet laser is fired into a vat of photopolymer resin to create torque-resistant ceramic parts able to endure extreme temperatures.

15.2.3.3 Additive manufacturing materials

It is possible to use many different materials to create 3D-printed objects. Many different metals and metal alloys are used in AM, from precious metals like gold and silver to strategic metals like stainless steel and titanium. AM technology fabricates jet engine parts from advanced metal alloys, and it also creates chocolate treats and other food items. Thermoplastic polymers remain the most popular class of AM materials. Acrylonitrile butadiene styrene (ABS), poly-lactic acid (PLA), and polycarbonate (PC) each offer distinct advantages in different applications. Water-soluble polyvinyl alcohol (PVA) is typically used to create temporary support structures, which are later dissolved away. A variety of ceramics have also been used in AM, including zirconia, alumina, and tricalcium phosphate. Also, alternate layers of powdered glass and adhesive are baked together to create entirely new classes of glass products. Biochemical healthcare applications include the use of hardened material from silicon, calcium phosphate, and zinc to support bone structures as new bone growth occurs. Researchers are also exploring the use of bio-inks fabricated from stem cells to form everything from blood vessels to bladders and beyond.

15.2.4 Augmented reality

Augmented reality (AR) is an extension of virtual reality, where the user, the IoT, and the computer interact in real time by adding layers of virtual information over a live camera feed into a headset display or through any other smart device. This gives the user the ability to view three-dimensional images of the physical environment (real) and with the digital (virtual) creating a mixed reality. AR is the real-time use of information in the form of text, graphics, audio, and other virtual enhancements integrated with real-world objects. It is this “real-world” element that differentiates AR from virtual reality. AR integrates and adds value to the user’s interaction with the real world, versus a simulation (Uva et al., 2018). Statistical analysis shows that the AR market will reach more than \$198.7 billion by 2025 (Liu, 2019). AR technology naturally has a stronghold in the video games and entertainment sector, but a growing number of manufacturing suppliers, including large automated equipment manufacturers, are utilizing the technology to provide their employees and customers with virtual hands-on instruction for operating machinery, troubleshooting, and conducting repairs. In fact, 10% of

Fortune 500 companies have already begun exploring shopping and operation applications for AR (Liu, 2019). There are three main realizations of AR in manufacturing:

- Head-mounted displays—for training and hands-free work;
- Handheld displays—for AR applications to provide real-time data;
- Spatial displays—to project virtual objects into the environment to assist product design.

15.2.4.1 Augmented reality for product design, inspection, and maintenance

Through virtual prototyping, product design engineers can study and test complex physics at a level of detail that was impossible through physical testing. AR provides an operational visualization of the device under design, improving the efficiency and usefulness of virtual prototyping. AR applications will provide workers with visual displaying of the parts and details to assemble, and information about the necessary instruments for every stage. They may highlight the finished pieces, giving the whole 3D instruction. And what is even more important, AR devices like smart glasses enables hands-free work. For industrial inspection and maintenance, AR can reduce task time and aid in detecting errors (Uva et al., 2018)

15.2.4.2 Augmented reality for upskilling and productivity

Aside from providing digital documentation for monitoring and repair of industrial maintenance operations, AR is providing upskilling technologies to help production workers. Upskilling is the integration between industrial workers and smart machines. Primarily, AR augments production workers' abilities to dramatically improve performance, provide industrial safety, and increase worker satisfaction. Examples of deployed upskilling technologies can be seen in the repair of industrial equipment, such as conveyor systems or automation production lines. Computer images, graphics, and text information can be displayed using headsets or mobile devices, such as smartphones and tablets. AR can also be deployed in wearable devices used in industrial and manufacturing facilities to increase worker productivity on a variety of installation, monitoring, and troubleshooting tasks. Delivering accurate data when needed is the real power behind using wearable AR devices within industrial and manufacturing settings. The information is presented in the technician's line of sight, leaving the production personnel's hands free so work can continue without interruption. Instead of having the most productive workers in the shop step away from the line to train up-and-comers, the new worker is able to learn and grow into their role without slowing down production by using AR technology (Uva et al., 2018).

15.2.4.3 Augmented reality for quality assurance

AR is not limited to training. Waiting for a licensed repairman may not be necessary if an AR-assisted repairman can identify problems and go through step-by-step



FIGURE 15.8 Application of augmented reality in advanced manufacturing systems ([Modern Machine Shop, 2019](#)).

repairs using his AR display. Quality assurance can be both faster and more accurate with AR devices identifying flaws in seconds, and assembling parts is simple thanks to step-by-step assistance from an AR device (see [Fig.15.8](#); [Uva et al., 2018](#)).

15.2.5 Simulation and virtual reality

Technological changes have made historic moves in the industry trajectory toward Industry 4.0. Simulation of the work environment is one of the effective tools in an automated robotic site. It contributes to a better work environment's awareness toward the machines' and robots' behavior, enhancement of the monitoring and troubleshooting of processes, and selection of the optimum adaptable design for the system ([Alasti et al., 2019](#); [Seyed-Hosseini et al., 2011a](#); [Badkoobehi et al., 2011](#)). Controlling robotic systems is a challenging task, especially when multiple robots are integrated to accomplish certain tasks for an automated manufacturing system. In the era of Industry 4.0, integrating virtual reality tools with real-time simulations can be very effective. In this way, various manufacturing system processes and robot motions can be simulated virtually. Such a virtual reality-based, task-level robot control system offers a great help for training of operators on a complex robotic system and robot control during hazardous/remote robot applications ([Novak-Marricincin et al., 2011](#); [Hempe and Rossmann, 2014](#); [Elahi et al., 2011e](#); [Seyed-Hosseini et al., 2011b](#)).

15.2.6 Cloud computing

Cloud computing is crucial for Industry 4.0 and is the underlying platform behind much of the digital disruption we have already observed. It is the ideal data storage resource for achieving smart factory interconnectivity. Cloud technology provides a centralized location for data that can be accessed from anywhere, allowing for improved connectivity and collaboration across multiple data sources. As industries move toward increased data sharing across departments and companies, cloud technologies will have to improve to achieve millisecond-scale reaction times. Improved reaction time will allow more machine data and control to be deployed to the cloud, enabling more data-driven services and remote-accessible production (BCG, 2019; Cochran et al., 2018). Not only is it scalable data storage, but it is the bedrock for supporting real-time data analysis, prediction, and machine learning. A 2016 survey by KPMG indicated that companies adopted cloud computing overwhelmingly to improve agility and responsiveness, accelerate product development and innovation, and save money. Due to these powerful advantages, cloud computing is now the preferred computing model for most technology enablement (Fig. 15.9).

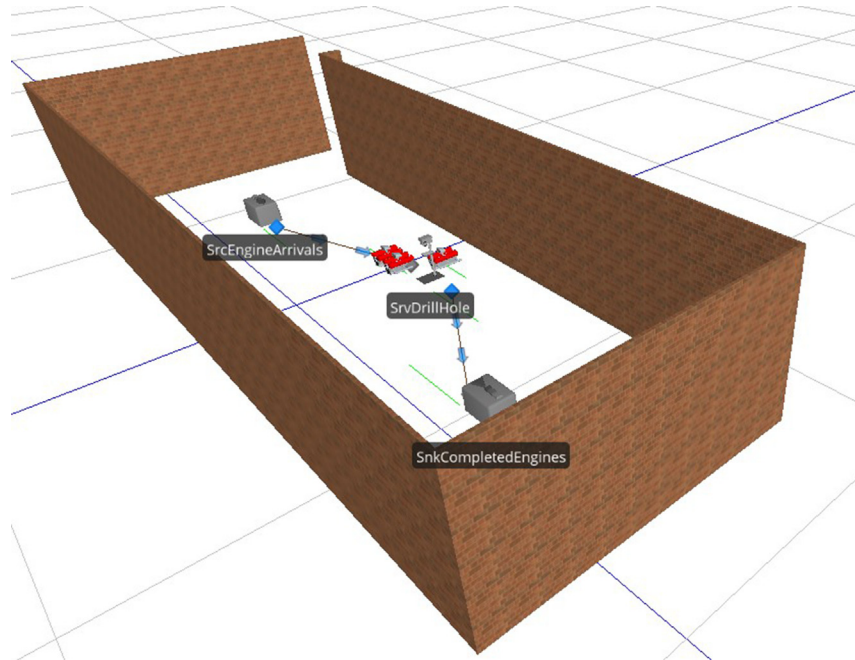


FIGURE 15.9 A virtual model of a manufacturing operation created in SIMIO Version 9.147 software environment.

Information and communication technology (ICT) is essential for the digitalization of the manufacturing sector (Cochran et al., 2017). Cloud computing represents a foundational, underlying platform technology that is key to enabling smart manufacturing. Cloud computing has permeated virtually all facets of the modern manufacturing enterprise and contributed to a transformation in how today's products are designed, made, and used. Cloud computing provides a myriad of benefits to large and small manufacturers, including: speeding up innovation cycle times, accelerating time to market, facilitating collaboration, supporting supply chain integration, enabling new business models, increasing operational efficiency, reducing costs, and increasing employee and customer satisfaction (Ezell and Swanson, 2017).

Cloud computing is a technology model for enabling the delivery of IT resources (i.e., servers, storage, applications, etc.) on demand. Cloud has essential characteristics such as on-demand self-service, resource pooling, and rapid elasticity—giving organizations the ability to purchase IT services in a utility-based model, paying for only the services consumed. Cloud also typically is delivered according to one of three service models, namely software as a service (SaaS, where the consumer uses a provider's application running on cloud infrastructure), platform as a service (PaaS, where the consumer can use cloud infrastructure to deploy applications) and infrastructure as a service (IaaS, where typically the consumer can provision IT resources and run their own systems and applications on infrastructure offered by a cloud provider). Additionally, cloud computing is usually deployed in one of four different configurations: a public cloud, a hybrid cloud, a community cloud, or a private cloud (Ezell and Swanson, 2017).

CloudiFacturing is a new term in digital manufacturing which refers to optimization of production processes and the ability to produce using cloud/high-performance computing (HPC)-based modeling and simulation. CloudiFacturing aims at leveraging online factory data and advanced data analytics, thus contributing to the competitiveness and resource efficiency of manufacturing SMEs, ultimately fostering the vision of Factories 4.0 and the circular economy.

15.2.7 Big Data and analytics

The rapid prevalence and potential impact of Big Data analytics platforms have sparked an interest amongst manufacturing systems. They are particularly well suited to benefit from data analytics platforms in their entire product lifecycle management for intelligent information processing, performing manufacturing activities, and creating value chains (Elahi and Franchetti, 2015b). Big Data analytics is the often complex process of examining large and varied data sets, or Big Data, to uncover information such as hidden patterns, unknown correlations, market trends, and customer preferences that can help organizations make informed business decisions. On a broad scale, data analytics technologies and

Table 15.1 The importance of advanced analytics of Big Data (Chen et al., 2012).

	Business intelligence	Advanced analytics
Answers the questions	• What happened? • When? • Who? • How many?	• Why did it happen? • Will it happen again? • What will happen if we change X? • What else does data tell us that we never thought to ask?
Includes	• Reporting (metrics) • Automated monitoring and altering • Dashboards • Online analytical processing (OLAP) • Ad hoc query • Operational and real-time business intelligence (BI)	• Statistical or quantitative analysis • Data mining • Predictive modeling • Multivariate testing • Big Data analytics • Text analysis

techniques provide a means to analyze data sets and draw conclusions about them which help organizations make informed business decisions. Business intelligence queries answer basic questions about business operations and performance (Zikopoulos and Eaton, 2011). Big Data analytics is a form of advanced analytics, which involves complex applications with elements such as predictive models, statistical algorithms, and what-if analysis powered by high-performance analytics systems (see Table 15.1; Chen et al., 2012).

Driven by specialized analytics systems and software, as well as high-powered computing systems, Big Data analytics offers various business benefits, including (Mazdeh et al., 2013; Akhavan et al., 2014; Seyed-Hosseini et al., 2010):

- New revenue opportunities;
- More effective marketing;
- Better customer service;
- Improved operational efficiency;
- Competitive advantages over rivals.

Big Data analytics applications enable Big Data analysts, data scientists, predictive modelers, statisticians, and other analytics professionals to analyze growing volumes of structured transaction data, plus other forms of data that are often left untapped by conventional BI and analytics programs. This encompasses a mix of semistructured and unstructured data (i.e., Internet clickstream data, web server logs, social media content, text from customer emails and survey responses, mobile phone records, and machine data captured by sensors connected to the IoT).

15.2.7.1 *Big Data analytics technologies and tools*

Unstructured and semistructured data types typically do not fit well in traditional data warehouses that are based on relational databases oriented to structured data sets. Further, data warehouses may not be able to handle the processing demands posed by sets of Big Data that need to be updated frequently or even continually, as in the case of real-time data on stock trading, the online activities of website visitors, or the performance of mobile applications. As a result, many of the organizations that collect, process, and analyze Big Data turn to NoSQL databases, as well as Hadoop and its companion data analytics tools, including (Hu et al., 2014):

- YARN: a cluster management technology and one of the key features in second-generation Hadoop;
- MapReduce: a software framework that allows developers to write programs that process massive amounts of unstructured data in parallel across a distributed cluster of processors or stand-alone computers;
- Spark: an open-source, parallel processing framework that enables users to run large-scale data analytics applications across clustered systems;
- HBase: a column-oriented key/value data store built to run on top of the Hadoop Distributed File System (HDFS);
- Hive: an open-source data warehouse system for querying and analyzing large data sets stored in Hadoop files;
- Kafka: a distributed publish/subscribe messaging system designed to replace traditional message brokers;
- Pig: an open-source technology that offers a high-level mechanism for the parallel programming of MapReduce jobs executed on Hadoop clusters.

15.2.7.2 *How Big Data analytics works*

Once the data are ready, they can be analyzed with the software commonly used for advanced analytics processes. This includes tools for (Hu et al., 2014):

- Data mining, which sift through data sets in search of patterns and relationships;
- Predictive analytics, which build models to forecast customer behavior and other future developments;
- Machine learning, which taps algorithms to analyze large data sets; and
- Deep learning, a more advanced offshoot of machine learning.

Big Data have become increasingly beneficial in supply chain analytics. Big supply chain analytics utilizes Big Data and quantitative methods to enhance decision-making processes across the supply chain. Specifically, big supply chain analytics expands data sets for increased analysis that goes beyond the traditional internal data found on enterprise resource planning (ERP) and supply chain management systems. Also, big supply chain analytics implements highly effective statistical methods on new and existing data sources. The insights gathered

facilitate better informed and more effective decisions that benefit and improve the supply chain (Hu et al., 2014).

15.3 Digital twin-driven smart manufacturing

Digital twin technology in manufacturing systems refers to a virtual representation of manufacturing elements such as personnel, products, assets, and process definitions, a living model that continuously updates and changes as the physical counterpart changes to represent status, working conditions, product geometries, and resource states in a synchronous manner. The digital representation provides both the elements and dynamics of how a physical thing operates and lives throughout its life cycle. Digital twin, acting as a mirror of the real world, provides a means of simulating, predicting and optimizing physical manufacturing systems and processes. Utilizing digital twin, together with intelligent algorithms, manufacturing systems can achieve data-driven operation monitoring and optimization, develop innovative product and services, and diversify their value creation and business models. Digital twin technology plays a pivotal role in the vision of smart manufacturing. It enables the shift from analyzing the past to forecasting the future.

15.3.1 A reference model for the digital twin

The features of a digital twin can be synopsized as real-time situation reflection, physical/cyber convergence and interaction, and self-evolution. In the manufacturing field, sensor-equipped machines could accumulate data in real time from the production system. By linking physical and cyberspace, the digital twin would reflect the system's real state. By updating data in real time, the model can undergo continuous improvement by comparing cyber space with physical space in parallel.

A digital twin reference model in a smart manufacturing system is shown in Fig. 15.10. It is critical to note that the represented reference model should be designed for flexibility and scalability in terms of analytics, processing, the number of sensors and messages, etc. in a given smart manufacturing system. This can allow the reference model to evolve rapidly with the continual, and sometimes exponential, changes in the industrial technologies (Zhang et al., 2019).

A digital twin technology offers an opportunity to simulate and optimize the production systems in smart manufacturing, including the logistical aspects, and enables a detailed visualization of the manufacturing process from single components up to the whole assembly. The digital twin advances the main disciplines of production systems (i.e., including production planning and control, maintenance, and layout planning) with the common target to increase competitiveness, productivity, and efficiency (Tao et al., 2019; Kritzinger et al., 2018).

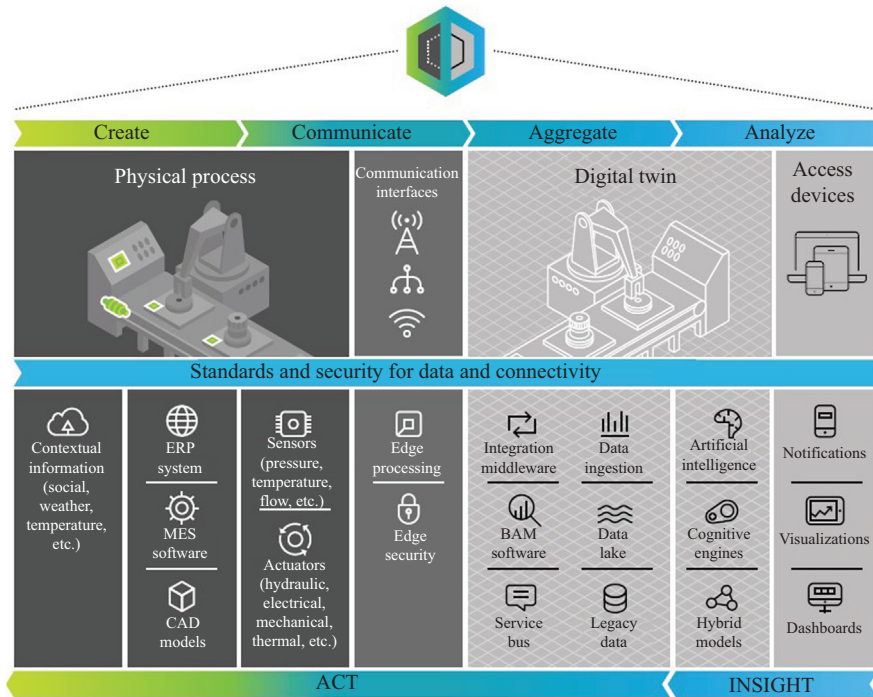


FIGURE 15.10 Digital twin reference model for smart manufacturing (Deloitte University Press, 2017).

The create phase incorporates outfitting the physical process with myriad sensors that measure critical inputs from the physical process and its surroundings (i.e., operational measurements with regard to the physical performance criteria of the productive asset including multiple works in progress, such as tensile strength, displacement, torque, and color uniformity and measurements on environmental or external data affecting the operations of a physical asset, such as ambient temperature, barometric pressure, and moisture level). The measurements can be transformed into secured digital messages by means of encoders and then transmitted to the digital twin. The signals from the sensors may be augmented with process-based information from systems such as the manufacturing execution systems, ERP systems, CAD models, and supply chains systems. This would provide the digital twin with a wide range of persistently updating data to be utilized as input for its analysis.

The communicate phase facilitates the seamless, real-time, bidirectional integration connectivity between the physical process and the digital platform. Network communication is one of the radical changes that have enabled the digital twin; it comprises three primary components including the following. (1) Edge interface: this connects sensors and process historians, processes signals

and data from them near the source, and passes data along to the platform. This serves to translate proprietary protocols to more easily understood data formats as well as reduce network communication. (2) Communication interfaces: these facilitate transfer information from the sensor function to the integration function. (3) Edge security, which refers to using firewalls, application keys, encryption, and device certificates.

The aggregate phase supports data assimilation into a data repository, processed and prepared for analytics. The data aggregation and processing may be done either on the premises or in the cloud.

In the analyze stage, data are analyzed and visualized. Data scientists and analysts can employ advanced analytics platforms and technologies to develop iterative models that generate insights and recommendations and guide decision-making.

In the insight phase, insights from the analytics are presented through dashboards with visualizations, highlighting unacceptable differences in the performance of the digital twin model and the physical world analogue in one or more dimensions, indicating areas that potentially need investigation and change.

The act phase is where actionable insights from the previous steps can be fed back to the physical asset and digital process to achieve the impact of the digital twin. Insights pass through decoders and are then fed into the actuators on the asset process, which are responsible for movement or control mechanisms, or are updated in back-end systems that control supply chains and ordering behavior—all subject to human intervention. This interaction completes the closed loop connection between the physical world and the digital twin. The digital twin application is usually written in the primary system language of the enterprise, which uses the above steps to model the physical asset and processes. In addition, throughout the process, standards and security measures may be applied for the purposes of data management and interoperable connectivity.

The digital twin conceptual model contains three primary components as it shown in Fig. 15.11:

1. A physical object in real space;
2. A virtual object in virtual space;
3. Data and information connections that converge the physical and virtual systems.

Fig. 15.12 represents an example of a digital twin for a sample robot arm: Meca500-R3, a six-axis robot arm. This robot arm has a maximum payload of 0.5 kg and a precision of 0.005 mm. Its total weight is 4.5 kg. Its operating voltage is 24 volts. It is equipped with a safety switch and controlled through the Internet via an Ether Cat connection. To program such a robot arm a web-based user interface that comes along with an animation of the motion of the robot arm is applied. Fig. 15.13 represents the end-effector motion when using the Move-Joints or Move-Pose commands for the Meca500-R3 robot arm.

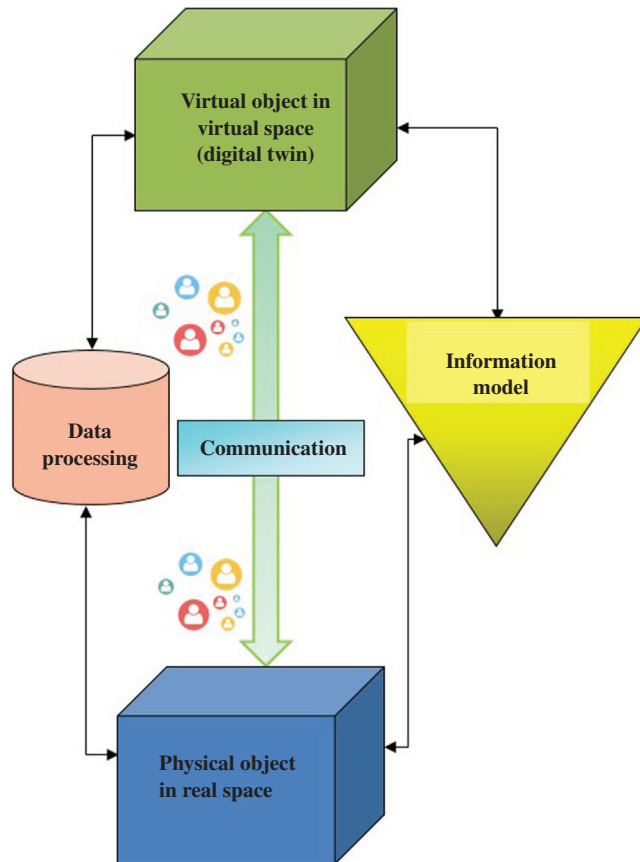


FIGURE 15.11 A digital twin conceptual model.

15.4 Creation of a digital twin in a smart manufacturing system

To create a digital twin in a smart manufacturing system, the following steps should be considered:

Forming a baseline: The digital twin creation starts with the process design. What are the processes and integration points for which the twin will be modeling? Standard process design techniques should be used to show how business processes, people enabling the processes, manufacturing applications, information, and physical assets interact. Diagrams are created that link the process flow to the applications, data needs, and the types of sensor information required to create the digital twin. The process design is augmented with attributes where cost, time, or asset efficiency could be improved. These typically form the baseline assumptions from which the digital twin enhancements should begin.

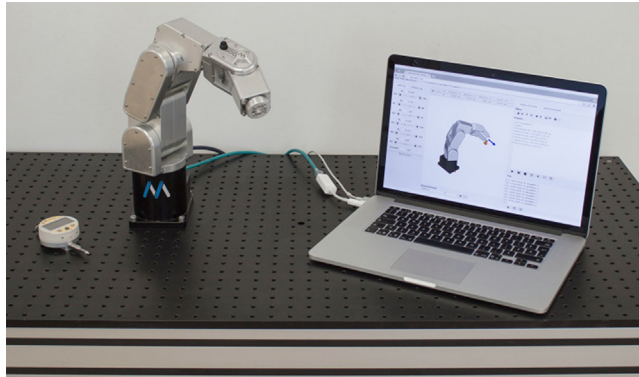


FIGURE 15.12 Digital twin of a Meca500-R3 robot arm.

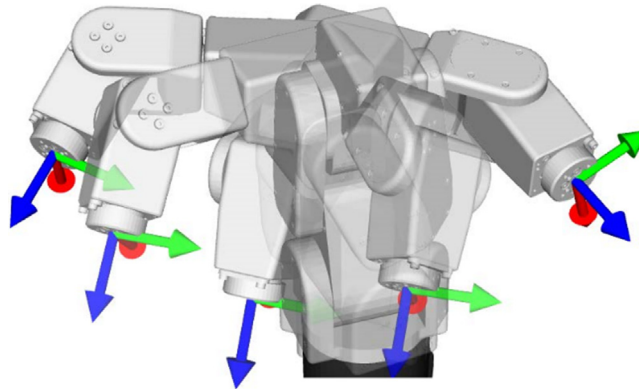


FIGURE 15.13 Schematic view for the end-effector motion in a Meca500-R3 robot arm when using the Move-Joints or Move-Pose commands.

Identifying the possibilities: The second step would be to shortlist a set of scenarios that could benefit from having a digital twin and answering the following questions:

- Is the product or manufacturing process being considered valuable enough for the manufacturing system to invest in building a digital twin?
- Are there outstanding, unexplained processor product-related issues that could potentially unlock value either for the customers or the manufacturing system?

Then each scenario would be assessed to identify pieces of the process that can provide quick wins by using a digital twin.

Identifying the pilot digital twin configuration: Operational, manufacturing, and organizational change management factors should be considered in identifying which configurations could be the best candidates for the pilot.



FIGURE 15.14 A digital twin for an assembling process created in SIMIO Version 9.147 software environment.

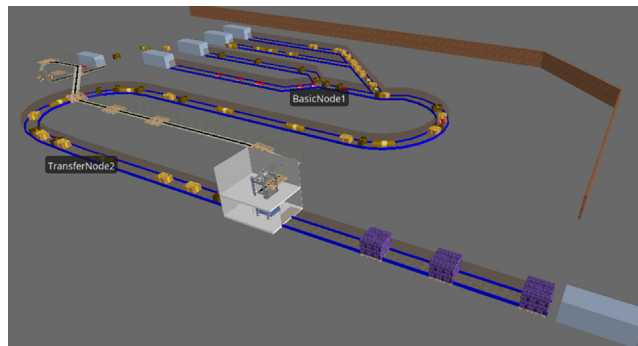


FIGURE 15.15 A digital twin for a packing system created in SIMIO Version 9.147 software environment.

Piloting a program: Moving quickly into a pilot program using iterative and agile cycles to accelerate learning, manage risk proactively, and maximize return on initial investments should be considered.

Scale the twin: Once successful, it can be important to identify opportunities to scale the digital twin. Target adjacent processes and processes that have interconnections with the pilot. Use the lessons learned from the pilot and the applied tools and techniques during the pilot to scale expeditiously.

Monitor and measure. Solutions should be monitored to objectively measure the value delivered through the digital twin. Identifying whether there were tangible benefits in cycle time, yield throughput, quality, utilization, incidents, and cost per item, among others is very critical. Making changes to digital twin processes iteratively, and observing results to identify the best possible configuration are key steps. [Figs.15.14](#) and [15.15](#) represents sample digital twins for assembling and packaging processes in order.

15.5 Summary

This chapter dealt with digital twin-driven smart manufacturing systems. The digital twin drives tangible value for smart manufacturing systems, creates new revenue streams, and helps them answer key strategic questions. With new technology capabilities, flexibility, agility, and lower cost, manufacturing systems will be able to start their journeys to create a digital twin with lower capital investment and shorter time to value than ever before. A digital twin has many applications across the life cycle of a product and real-time simulation of manufacturing processes in smart manufacturing systems. This chapter verifies that the digital twin provides an effective way for the cyberphysical integration of manufacturing.

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Mathematical models for the dimensional accuracy of products generated by additive manufacturing

16

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16.1 Introduction to dimensional quality in additive manufacturing

The new paradigm of Industry 4.0, also denoted as digital transformation or connected industry, implies promising future opportunities for companies of numerous sectors in the market and a revolutionary transformation of the tasks to be developed by many companies in their economic activity. Additive manufacturing

(AM) can be described as one of the most relevant tools that are comprised inside the emergent technologies of this new paradigm. With regards to these new manufacturing methods, the factories of the future need production engineers with solid skills of the technical requirements that can be guaranteed in products generated by AM in terms of dimensional accuracy, and for this reason this chapter will be focused on these topics.

AM comprises a field of distinct manufacturing processes that are oriented to generate the final part by joining the different portions of the initial material according to the geometry defined in a 3D model of the part. This material joining is usually carried out by deposition of the material layer-by-layer or by other different technologies that also exist for these purposes, such as using local heating to melt the initial material, etc. These technologies imply a great revolution for the manufacturing industry, as they allow to obtain directly the desired part from a 3D model, instead of needing other manufacturing methods such as cutting, material forming, molding, and welding (Meneghetti et al., 2019).

There are different terms that can be found in the bibliography for making reference to AM, such as mainly rapid prototyping (RP), rapid tooling (RT), 3D printing, or solid freeform manufacturing (Krujatz et al., 2017; Niaki and Nonino, 2017). The terminology commonly accepted for these manufacturing processes is defined in the ISO/ASTM 52900 standard published in 2015. It replaced the ASTM F2792 standard, which was edited in 2012 also for this purpose (ISO/ASTM 52900:2015, 2015; ASTM F2792, 2013).

The origin of AM dates back to the 1980s, when the engineer Charles Hull patented in the United States a new device that made possible the manufacturing of three-dimensional parts by stereolithography (SL). This invention was based on printing thin layers of photo-sensible material and using ultraviolet light to cure this material. In this way, the desired parts could be manufactured layer-by-layer from 3D models that were previously constructed by computer-aided design (CAD) or computer-aided manufacturing (CAM) (Krujatz et al., 2017; Niaki and Nonino, 2017; Gardan, 2016; Wong and Hernandez, 2012; Bandyopadhyay and Bose, 2015; Hull, 1986).

In 1986, Charles Hull founded in the United States the company 3D Systems, and in 1987 presented the SLA-1 as the first commercial 3D printer. Moreover, he created STL (the acronym for “standard triangle language”), as the file format to be used for generating the part geometry in the 3D models needed for these manufacturing equipments (Krujatz et al., 2017; Bandyopadhyay and Bose, 2015; Zhang and Jung, 2018).

More recently, many other companies also have launched other solutions to produce prototypes or parts by similar technologies. The great variety of commercial devices that exist nowadays makes it possible to choose among techniques that allow different levels of process accuracy and functionalities, and that are more adequate for certain types of materials such as rubber, resins, metals, and ceramics (Luis Pérez et al., 2001).

The successive phases of AM techniques comprise the definition of a 3D model by a CAD/CAM software or by a 3D scanner, conversion of the CAD model to another file that will be introduced in the AM machine (usually in STL file format), and execution of the AM process according to the part geometry described in this file. The most common file format to operate AM machines is STL, but there are also other alternatives that can be applied such as OBJ, AMF, 3MF, or PLY.

Software is also needed that will be responsible for executing the STL files by the AM machine, which is known as slicing software. There are several versions of this type of software, and the best alternative depends on the AM technology that will be employed. This software will orientate the part according to the manufacturing direction, and then will slice the CAD model into cross-sectional layers. Later, it is evaluated whether each layer will be produced on the previous layer, or on the contrary the construction of supports will be needed. Finally, the slicing software will translate the CAD model using another specific file that can be executed by the AM machine, which will be usually expressed in G-code language (Niaki and Nonino, 2017; Bandyopadhyay and Bose, 2015; Chua and Leong, 2017; Srivatsan and Sudarshan, 2015).

With the purpose of developing technical guidelines for these processes, some specialized committees and working groups have been created. For example, AM-platform (<https://www.rm-platform.com>) was constituted in 2007 as a community of stakeholders in the field of AM. The ASTM F42 committee appeared in 2009 to define the specific standards that could be required for AM technologies, while the ISO Technical Committee 261 (ISO/TC261) was established in 2011 for standardization of the different technologies, test procedures, quality parameters, etc. (ASTM F2792, 2013; ISO/ASTM 52900:2015, 2015).

In 2016, America Makes and the American National Standards Institute (ANSI) launched the America Makes & ANSI AM Standardization Collaborative (AMSC), as an institution interested in developing standards and specifications based on the needs of stakeholders, and promoting these technologies in the industry (America Makes & ANSI Additive Manufacturing Standardization Collaborative AMSC, 2018).

Among the numerous advantages of AM in comparison to conventional manufacturing methods, the decrease in material and energy requirements, the possibility of generating products with customized geometries, the capability of producing single parts or small batches, the decrease in required working space, and the quick response to geometry modifications in the part design can be highlighted. However, these technologies also present some limitations such as the reduced working size of commercial machines, the moderate levels of dimensional accuracy and surface finish, and the extensive production times to generate the complete part, although they are valid for certain applications (Niaki and Nonino, 2017; Srivatsan and Sudarshan, 2015; Townsend et al., 2016).

AM can be described as the technologies that have exhibited the fastest growing in recent years (Chua et al., 2017). In this sense, the Wohlers Report 2018

quantified an approximately 80% increase in sales of AM machines during the period 2016–2017 (Wohlers Report, 2018). The great development of these manufacturing technologies can be attributed to the increasing interest in different sectors such as aerospace, defense, medical, dental, and automotive.

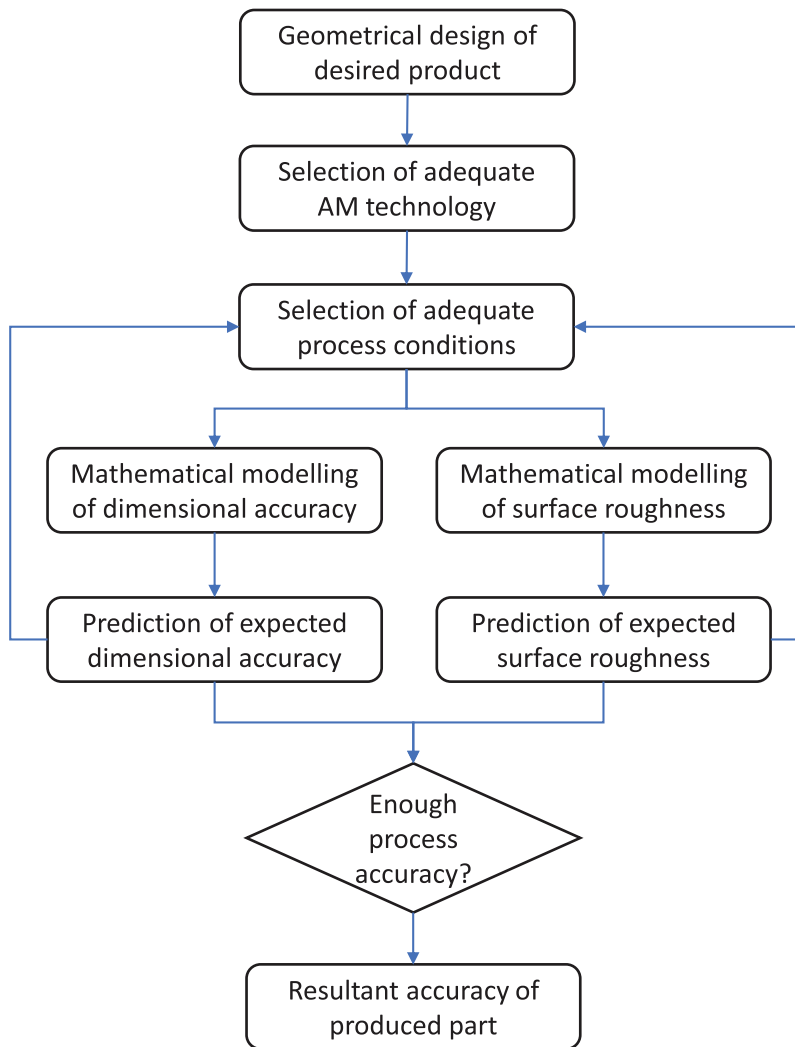
Nevertheless, its application in industry to produce functional parts is not easy as a consequence of the limitations including the impossibility of achieving better geometrical and surface accuracy, the lower mechanical properties of the final parts, the need for a supporting framework for many product designs, etc. (Lieneke et al., 2016; Moylan et al., 2012a). As an example, NASA explained that the introduction of AM in their production systems has been slow due to the absence of broadly accepted materials and quality systems for these processes, and nondestructive evaluation techniques integrated into the AM machines (Walter et al., 2015).

In order to evaluate whether the products obtained by AM will satisfy the requirements established in terms of dimensional accuracy, the appropriate AM technology and process parameters must be chosen, and specific mathematical models should be applied to check the expected performance of these free-form manufacturing methods, as illustrated in Fig. 16.1.

The stages of selecting the AM technology for each specific application and selecting the process conditions that could guarantee the desired dimensional quality have a crucial relevance in the decision-making to be carried out by production engineers along the product manufacturing cycle. In this sense, the application of mathematical models such as those that will be described in this chapter is essential to enhancing the AM machine behavior and to satisfy the product requirements.

There are diverse criteria that can be adopted to classify the distinct AM technologies, such as the type of raw material, the process functioning principles, and the initial shape or state of the material. As can be observed in the ISO/ASTM 52900 standard, technical committee ISO/TC 261 dedicated to AM, in collaboration with the technical committee ASTM F42 on AM technologies, established a classification of these processes into the following seven categories: binder jetting (BJ), which represents the processes with a liquid bonding agent that will be selectively deposited for joining the initial powder materials; directed energy deposition (DED), in which the raw materials are fused by a focused thermal energy as material deposition is produced; material extrusion (ME), based on selective dispensation of raw material through a nozzle or orifice; material jetting (MJ), in which the material is selectively deposited by droplets; powder bed fusion (PBF), in which thermal energy is used to selectively fuse the required regions of the powder bed; sheet lamination (SL), based on bonding of material sheets to generate the final part; and vat photopolymerization (VP), in which light-activated polymerization is used to selectively cure the liquid photopolymer in a vat (ISO/ASTM 52900:2015, 2015; Froes and Boyer, 2019; Lee et al., 2017).

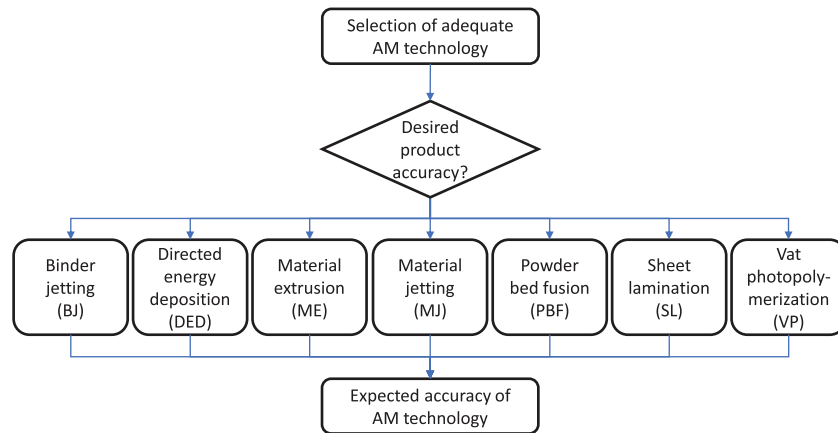
Fig. 16.2 represents a basic scheme about the decision-making that must be executed by production engineers with regards to the selection of the AM method that could be more recommendable for each specific application. The different

**FIGURE 16.1**

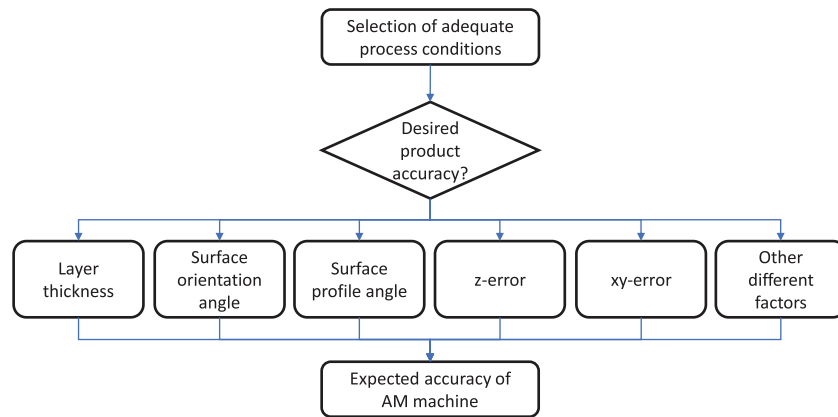
Schematic representation of the basic stages for process optimization in additive manufacturing.

types of existing AM technologies are contained in this figure, through the seven categories that have been mentioned above.

Among the main factors that will influence the dimensional quality of AM-generated parts, Fig. 16.3 highlights only some of the process conditions reflected in the mathematical models that can be found in the specialized bibliography about product accuracy in AM, as will be explained below. The layer thickness,

**FIGURE 16.2**

Schematic representation of the technology selection stage for process optimization in additive manufacturing.

**FIGURE 16.3**

Schematic representation of the process condition selection stage for process optimization in additive manufacturing.

surface orientation angle, surface profile angle, z-error, xy-error, beam offset, lamination borders, penetration depth, extruder errors, fused deposition borders, layer composition, particle adhesion, and other different factors are studied by the algorithms that will be described in this chapter.

In general terms, different factors such as the layer thickness, build orientation, deposition speed, feed rate, process temperature, raw material, infill pattern, STL file properties, and AM technology should be analyzed in order to assure the

desired quality of the final part (Lee et al., 2017; Calignano et al., 2017; Attoye et al., 2018; Mohamed et al., 2015). These factors can influence not only the dimensional accuracy but also the mechanical properties of produced parts, including dimensional and geometrical deviations, surface roughness, porosity, other internal defects, residual stress, balling effect, etc. (Chua et al., 2017). In order to guarantee an adequate process performance, specific design rules must be followed for each AM technology (Calignano et al., 2017).

There are many works dedicated to determining the relationship between these factors and the product properties or to deducing the optimized values that should be adopted for these factors. In some of these studies certain analysis techniques such as design of experiments (DOE) or analysis of variance (ANOVA) were applied (Attoye et al., 2018; Lieneke et al., 2015; Udroui et al., 2019). The process parameters to be selected must be studied for each product design, in order to determine the set of process conditions that will provide the expected dimensional quality in the final part (Nozar et al., 2017).

To identify the dimensional accuracy that can be achieved through distinct AM technologies or machines, not only the evaluation of parts and machines for each specific process, but also the measuring of benchmark artifacts can be applied. There are different types of benchmark artifacts that have been developed for this purpose by a number of authors (Moylan et al., 2012a,b; Calignano et al., 2017).

These artifacts serve to determine the capabilities and limitations of each AM process, and to compare the expected properties of products generated through distinct alternatives. Moreover, they are very useful to demonstrate the performance of different AM machines without the need for specialized measuring equipment (Chua et al., 2017; Moylan et al., 2012a,b; Rebaioli and Fassi, 2017; Rivas Santos et al., 2018). For example, Barari et al. (2017) conceived a test specimen with several ramp surfaces of distinct slopes, and it is very helpful to discuss the effect of the surface orientation angle on the achievable surface finish for constant values of layer thickness, process speed, and material properties.

Another method that can be applied to analyze these processes is numerical modeling, and both experimental and theoretical studies can serve to deduce mathematical expressions that could represent the relationship between the dimensional accuracy or surface roughness and the main process parameters. In the following sections, the factors that present a higher influence on the achievable dimensional quality will be identified, and after that the main mathematical models that can be adopted to describe the process performance will be explained.

16.2 Main factors for dimensional accuracy in additive manufacturing

Due to the great interest that Industry 4.0, also called digital transformation or connected industry, inspires nowadays in the majority of companies of distinct

sectors, exhaustive training is required about the fundamentals and applications of the emergent technologies that are promoted by this new paradigm. Among these new tools, the factories of the future need a solid knowledge about the dimensional precision that can be achieved in AM-generated parts.

The dimensional quality of parts produced by AM is influenced by diverse factors, which include among others possible deviations in CAD model processing, the process parameter settings, the AM process execution, machine errors, and material shrinkage (Zhu et al., 2017). Each type of free-form manufacturing technology can imply specific factors to be considered, according to the physical phenomena that take place during material processing.

In this section, among the different factors related to the dimensional accuracy and surface finish of AM-generated parts, the influence of the layer thickness, extruder errors, build orientation, material shrinkage, and other related parameters will be analyzed.

16.2.1 Effects of layer thickness and surface orientation

Since AM consists of layer-by-layer processes, the produced parts can show some geometric defects in the form of gaps as a consequence of the process execution, although they were not present on the CAD design. The size of these geometric imperfections will depend on the values selected for layer thickness and surface orientation. This physical phenomenon is known as the staircase effect, and could have a relevant influence on the dimensional accuracy and surface roughness of the final products.

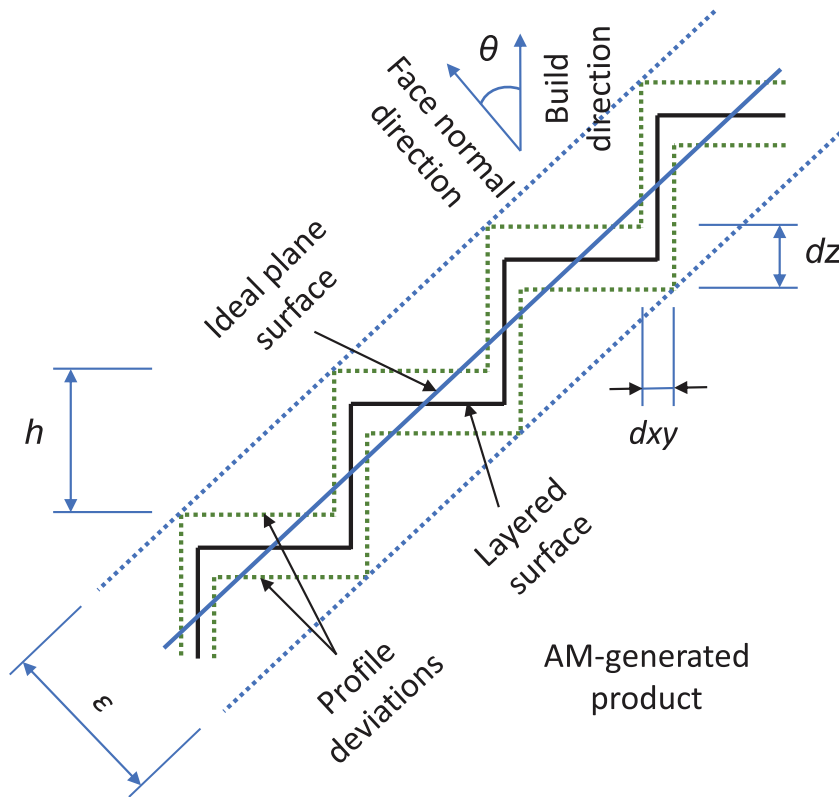
As reported by several authors, there are certain mathematical expressions that can be used to estimate the dimensional deviations caused by the staircase effect as a function of process parameters such as the layer thickness (h) and the surface orientation angle (θ) (Arni and Gupta, 2001; Ahn et al., 2009; Pandey et al., 2003).

The following model can be applied to deduce the flatness error of planar faces as a consequence of the staircase effect according to Arni and Gupta (2001) although in a more integrated form, and including different formulations depending on the values selected for the surface orientation angle as argued by these authors:

$$\begin{aligned}\varepsilon_{\text{fla}} &= \delta z \quad \text{for } 0 \leq \theta \leq \theta_{cr} \text{ or } \pi - \theta_{cr} \leq \theta \leq \pi \\ \varepsilon_{\text{fla}} &= (h + \delta z)\cos\theta + (\delta xy)\sin\theta \quad \text{for } \theta_{cr} < \theta \leq \pi/2 \\ \varepsilon_{\text{fla}} &= -(h + \delta z)\cos\theta + (\delta xy)\sin\theta \quad \text{for } \pi/2 < \theta \leq \pi - \theta_{cr}\end{aligned}\tag{16.1}$$

where h is the layer thickness, δz is the z -error, δxy is the xy -error, θ is the surface orientation angle, which corresponds to the angle between the face normal direction with regards to the part surface and the build orientation assumed during the AM, and θ_{cr} is the critical value of the surface orientation angle, which will imply the occurrence of the staircase effect.

The meaning of these process parameters is illustrated in Fig. 16.4, which shows a basic scheme of the typical surface profile that is originated by these free-form manufacturing techniques. The stair profile that characterizes the

**FIGURE 16.4**

Schematic representation of the staircase effect in additive manufacturing processes.

surface of the parts subjected to AM processes can be observed in this figure, as well as the errors that can occur along the x , y , and z machine axes.

According to this equation, the flatness error will be affected by the layer thickness, surface orientation angle, z -error, and xy -error in the case of intermediate values of surface orientation angle. Nevertheless, these deviations will be given exclusively by the z -error if the face normal direction and build orientation are collinear, or by the xy -error if the face normal direction and build orientation are located in perpendicular directions.

In the particular case of negligible values of z -error and xy -error and low values of surface orientation angle, the previous equation could be simplified as follows, as reported by Paul (2013):

$$\varepsilon_{\text{fla}} = h \cos \theta \quad (16.2)$$

Similar mathematical expressions could also be employed to estimate other geometrical errors associated with the AM-generated parts, such as the cylindricity,

angularity, perpendicularity, parallelism, conicity, or total runout errors, as will be described below.

In the case of the cylindricity error, the following expression could be applied, according to Paul (2013):

$$\varepsilon_{\text{cyl}} = h \sin \theta_{\text{cyl}} \quad (16.3)$$

where θ_{cyl} is the surface orientation angle for cylindrical surfaces, which is defined between the face normal direction for the cylindrical surface and the build orientation.

As reported by Das et al. (2015), the angularity, perpendicularity, and parallelism errors of produced parts can also be estimated by simplified mathematical expressions like the following equations:

$$\varepsilon_{\text{ang}} = h \cos \theta_{\text{ang}} \quad (16.4)$$

$$\varepsilon_{\text{per}} = h \cos \theta_{\text{per}} \quad (16.5)$$

$$\varepsilon_{\text{par}} = h \cos \theta_{\text{par}} \quad (16.6)$$

where θ_{ang} , θ_{per} , and θ_{par} are the surface orientation angle for the angularity, perpendicularity, and parallelism errors, respectively.

More detailed expressions were also suggested for these geometrical deviations by other authors, but these simplified equations can be applied to predict the angularity, perpendicularity, and parallelism errors from the process parameters.

A similar expression can be also adopted to evaluate the conicity error in components produced by free-form processes according to Das et al. (2015):

$$\varepsilon_{\text{con}} = h \sin \theta_{\text{con}} \quad (16.7)$$

where θ_{con} is the surface orientation angle for conical surfaces, which is conceived as the angle between the cone generator and the build orientation. This parameter of AM-generated parts can be expressed as $\theta_{\text{con}} = \theta + \alpha$, where θ is the angle between the cone axis and the build orientation, while α is the cone semi-angle.

Another deviation that could be necessary to determine on the part surface is the total runout error, which corresponds to the maximum deviations that can be detected in the entire surface. According to Paul (2013), the total runout error can be calculated by the following expression:

$$\varepsilon_{\text{tot_run}} = \max(d_i) - \min(d_i) \quad (16.8)$$

where d_i is the distance between the i -th point on the part surface and the reference axis that can be assumed for this surface.

A mathematical expression similar to those indicated previously for other geometrical deviations can be also applied to calculate the total runout error, as will be shown below:

$$\varepsilon_{\text{tot_run}} = h \sin \theta_{\text{tot_run}} \quad (16.9)$$

where $\theta_{\text{tot_run}}$ is the surface orientation angle for total runout error, which is established as the angle between the reference axis and the build orientation.

16.2.2 Effects of extruder errors

The extruder errors are one of the main factors that affect the dimensional quality of parts obtained by free-form manufacturing processes based on fused deposition modeling (FDM). Similar deviations could be analyzed in the case of other AM technologies. These deviations include the position errors associated with the machine motors, and the processing errors caused by the transformations originated on the material.

The following equations can be employed to predict the position errors of machine extruder as suggested by Wang et al. (2017) although with a slightly different formulation:

$$e_{\text{px}}(x, y) = e_{\text{px,lin}}(x, y) + e_{\text{px,vol}}(x, y) + \varepsilon_x \quad (16.10)$$

$$e_{\text{py}}(x, y) = e_{\text{py,lin}}(x, y) + e_{\text{py,vol}}(x, y) + \varepsilon_y \quad (16.11)$$

where (x, y) are the coordinates of extruder position at the direction of the x and y machine axes, $e_{\text{px,lin}}(x, y)$ and $e_{\text{py,lin}}(x, y)$ are the linear terms of extruder position errors, which will be given by the deviations evidenced on the machine movements in both x or y axes directions, $e_{\text{px,vol}}(x, y)$ and $e_{\text{py,vol}}(x, y)$ are the volumetric terms of extruder position errors, which represent the main deviations of machine movements with regards to a linear pattern, and ε_x or ε_y are the uniformly distributed terms of extruder position errors, which correspond to the variability registered on the volumetric errors.

The linear terms of extruder position errors are attributed to the linear deviations that can be produced on the machine axes displacement. The linear effects of material shrinkage could be also added to these deviations during modeling of the overall dimensional accuracy in these free-form manufacturing processes. These linear terms can be modeled by the following expressions:

$$e_{\text{px,lin}}(x, y) = a_{x0} + a_{x1}x + a_{x2}y \quad (16.12)$$

$$e_{\text{py,lin}}(x, y) = a_{y0} + a_{y1}x + a_{y2}y \quad (16.13)$$

where a_{x0} , a_{x1} , a_{x2} , a_{y0} , a_{y1} , and a_{y2} consist of constant coefficients that can be determined by regression analysis from the positions adopted by the machine extruder during the movement of the machine axes.

On the other hand, the volumetric terms of extruder position errors and the uniformly distributed terms of extruder position errors that also appear in this mathematical modeling could be estimated from the overall deviations originated during these AM processes.

The following equation can be used to estimate the shape deviations originated on the part surface as a consequence of the position errors associated to the

extruder of the AM machine:

$$\Delta r(\gamma) = \beta_0 r(\gamma) + \sum_{i=2}^N \left[\beta_{1i} r(\gamma) \sin(k\gamma) + \beta_{2i} r(\gamma) \cos(k\gamma) \right] + \varepsilon_\gamma \quad (16.14)$$

where $r(\gamma)$ is the real location of the points on the part surface caused by the AM process, β_0 is a coefficient related to the location-independent deviations that describe the average shape deviations of produced part, β_{1i} and β_{2i} are constant coefficients that correspond to the location-dependent deviations provoked by the extruder errors, and ε_γ is an unpredictable high-frequency error that can also influence the shape deviations of the final part.

16.2.3 Effects of material shrinkage and beam offset

The parts produced by free-form manufacturing processes can experience material shrinkage as a consequence of the thermal variations originated during the layer deposition. The material shrinkage in these manufacturing processes is associated with the process parameters, material density, and room temperature.

Material shrinkage can be deduced by comparison between the theoretical size of the AM-generated part according to the CAD model, and its real size as a result of the physical phenomena involved in the AM. The shrinkage experienced by the produced part in the longitudinal and radial directions can be defined by the following equations (Vangapally, 2017):

$$s_l(\%) = \frac{l_{real} - l_{theo}}{l_{theo}} 100 \quad (16.15)$$

$$s_r(\%) = \frac{d_{real} - d_{theo}}{d_{theo}} 100 \quad (16.16)$$

where l_{real} and d_{real} are the real values of the length and diameter of the produced part, while l_{theo} and d_{theo} represent the theoretical values that are reflected in the CAD model.

In laser-based AM processes, not only the material shrinkage but also the laser beam can imply a certain variation in the resultant size of the final part with regards to the theoretical size of the CAD model. The following expressions can be employed to determine the average shrinkage s and beam offset b (Mahesh, 2004):

$$s = \frac{1}{n-1} \sum_{i=2}^n \frac{l_{real1} - l_{reali}}{l_{theo1} - l_{theoi}} - 1 \quad (16.17)$$

$$b = \frac{l_{real1}}{n-1} \sum_{i=2}^n \frac{l_{theo1} - l_{theoi}}{l_{real1} - l_{reali}} - l_{theo1} \quad (16.18)$$

where l_{real} is the real value of the length of the AM-generated part and l_{theo} corresponds to the theoretical value contained in the CAD model.

A benchmarking can be also applied to evaluate the material shrinkage and laser beam in parts obtained by RP technologies, and it could serve to compare distinct techniques such as SLA, SLS, FDM, and LOM.

Other authors, like [Huang et al. \(2015\)](#), have proposed another model to estimate the material shrinkage in radial direction. The following expression based on a Fourier series is employed in this mathematical model to describe the material shrinkage that takes place in AM-generated parts:

$$s = c + \sum_k [a_k \cos(k\gamma) + b_k \sin(k\gamma) + \varepsilon_\gamma] \quad (16.19)$$

where c represents the global deviation in the entire part, γ is the position angle in the cross-section, and ε_γ is the unexpected variability in radial direction, while a_k and b_k are constants that depend on the material properties and other related factors. The parameters c , a_k , and b_k contained in this equation are influenced by the effective part radius.

For certain process conditions such as those considered in the work of [Huang et al. \(2015\)](#), the previous equation can be simplified to the following expression, or a different simplified expression could be deduced depending on the AM technology, material type, and process parameters:

$$s = \alpha_1 r_0^a + \alpha_2 r_0^b \cos(2\gamma) + \varepsilon_\gamma \quad (16.20)$$

where r_0 is the effective part diameter, and α_1 , α_2 , a , and b are constants that depend on the material properties and other factors of the free-form manufacturing process.

When the shrinkage is highly conditioned by the cure of material at the different surface positions, the following integral expression can be applied to estimate the average shrinkage on the part contour as proposed by [Bikas et al. \(2016\)](#) for laser-based processes such as the SLA techniques:

$$s = \frac{1}{L} \int_0^L s_r(y) dy \quad (16.21)$$

where $s_r(y)$ is the residual shrinkage at surface position y , and s is the average shrinkage due to the cure of material.

16.3 Mathematical modeling of dimensional deviations in additive manufacturing

In this section, the main mathematical models that could be applied to predict the dimensional and geometrical accuracy and surface integrity of the parts produced by AM will be described. The relationship between the main process parameters and the achievable dimensional quality will be expressed by these models, and they would serve to choose the process conditions that allow enhancement of the AM process performance.

16.3.1 Dimensional deviations in additive manufacturing-generated parts

In AM, it is crucial to understand the relationship between the dimensional deviations that appear on the final part surfaces and the factors involved in these free-form manufacturing processes, in order to improve the dimensional accuracy of produced parts by the appropriate process parameter settings.

The geometric and surface irregularities that are originated during the AM process can be determined by comparing the dimensional properties of the final part and the theoretical properties of the CAD model. For a simplified estimation of the dimensional accuracy of the AM-generated parts, the following expression can be employed (Deckers et al., 2011):

$$\Delta l(\%) = \frac{|l_{real} - l_{theo}|}{l_{theo}} 100 \quad (16.22)$$

where l_{real} represents the dimensional property measured experimentally on the manufactured part, and l_{theo} is the expected value contained in the CAD model for this dimensional property.

For a detailed analysis of the dimensional quality of the parts produced by free-form manufacturing processes, there are different mathematical models that can be used to understand the influence of the diverse factors involved in these processes and the dimensional deviations that can appear on the final part. The main models that exist for this purpose will be explained in this section.

In order to evaluate the dimensional accuracy of the AM machines, Brajliah et al. (2011) recommend the utilization of a cube-shape test part with three pairs of spherical holes. Each pair of spherical holes is located at a different face of the test part, and is aligned to a specific machine axis. This test part allows to estimate by separating the errors of the different machine axes, which is convenient due to each axis exhibiting distinct error levels.

The procedure proposed by these authors consists of measuring the location of all the spheres of the test part, and determining the vectors that represent the distance between each pair of spherical holes. These vectors will serve to deduce the linear errors associated with each machine axis, as is explained below.

The vectors that describe the distance between the centers of both spheres aligned with the same machine axis, can be deduced as follows:

$$\begin{aligned} \vec{r}_x &= (x_{x2} - x_{x1}, y_{x2} - y_{x1}, z_{x2} - z_{x1}) \\ \vec{r}_y &= (x_{y2} - x_{y1}, y_{y2} - y_{y1}, z_{y2} - z_{y1}) \\ \vec{r}_z &= (x_{z2} - x_{z1}, y_{z2} - y_{z1}, z_{z2} - z_{z1}) \end{aligned} \quad (16.23)$$

where $\vec{r}_x$, $\vec{r}_y$, and $\vec{r}_z$ are the vectors for each machine axis, while (x_{1i}, y_{1i}, z_{1i}) and (x_{2i}, y_{2i}, z_{2i}) are the coordinates of the center of the first and second spheres aligned with the i -th machine axis.

From these vectors, the linear errors in each machine axis can be calculated by comparing these experimental measures with the theoretical distance between both spheres according to the CAD model, using the following equations:

$$\begin{aligned}\Delta x &= r_x - d \\ \Delta y &= r_y - d \\ \Delta z &= r_z - d\end{aligned}\quad (16.24)$$

where r_x , r_y , and r_z refer to the vector modulus that correspond to the linear deviation on the x , y , and z axis respectively, and d is the theoretical value of the distance between the spheres aligned with each machine axis.

This procedure also includes detection of the angular deviations that can be present in the linear axes of the AM machines, such as the squareness errors originated by the angle between each pair of vectors of the test part. The angle between each pair of machine linear axes can be estimated by the following mathematical expressions:

$$\begin{aligned}\alpha_{xy} &= \arccos\left(\frac{x_{r_x}x_{r_y} + y_{r_x}y_{r_y} + z_{r_x}z_{r_y}}{r_x r_y}\right) \\ \alpha_{yz} &= \arccos\left(\frac{x_{r_y}x_{r_z} + y_{r_y}y_{r_z} + z_{r_y}z_{r_z}}{r_y r_z}\right) \\ \alpha_{zx} &= \arccos\left(\frac{x_{r_z}x_{r_x} + y_{r_z}y_{r_x} + z_{r_z}z_{r_x}}{r_z r_x}\right)\end{aligned}\quad (16.25)$$

where (x_{ri}, y_{ri}, z_{ri}) are the components of the different deviation vectors of the test part along the direction of x , y , and z linear axes of the additive manufacturing machine.

From the angles represented by these equations, the squareness errors that could exist between each pair of machine linear axes can be determined as follows:

$$\begin{aligned}\Delta\alpha_{xy} &= \alpha_{xy} - 90\text{degrees} \\ \Delta\alpha_{yz} &= \alpha_{yz} - 90\text{degrees} \\ \Delta\alpha_{zx} &= \alpha_{zx} - 90\text{degrees}\end{aligned}\quad (16.26)$$

The linear and angular deviations defined in the previous equations will contribute to the dimensional irregularities that can be detected on the part surface in different directions according to the local coordinate system of the manufactured part.

The mathematical model proposed by [Zhu et al. \(2017\)](#) can be used to estimate the dimensional deviations on the part surface:

$$\Delta r(\gamma) = r(\gamma) - r_0(\gamma) + \varepsilon_\gamma \quad (16.27)$$

where $r(\gamma)$ is the real position of each point of the part surface expressed in a polar coordinate system, $r_0(\gamma)$ is the theoretical position for the different surface

points according to the CAD model, and ε_γ represents a fluctuating error provoked by other stochastic circumstances that could occur during the free-form manufacturing process. An estimator of the fluctuating error ε_γ can be considered for this model, while the theoretical position of the different surface points $r_0(\gamma)$ is given by the geometry design of the CAD model.

A Fourier series can be employed to determine the resultant positions of surface points $r(\gamma)$, and then the following mathematical expression can be adopted to evaluate the surface accuracy:

$$\Delta r(\gamma) = c_0 + \sum_{k=1}^N [a_k \cos(k\gamma) + b_k \sin(k\gamma)] - r_0(\gamma) + \varepsilon_\gamma \quad (16.28)$$

where c_0 , a_k , and b_k are constant coefficients needed to estimate the position of each point on the part surface in the polar coordinate system.

Other mathematical algorithms such as the equations contained in the previous section, can be also considered for predicting the dimensional and geometrical irregularities of the mechanical parts subjected to AM.

16.3.2 Surface roughness in additive manufacturing-generated parts

Several studies have focused on the analysis of surface roughness in mechanical parts produced by free-form manufacturing processes, as an important aspect of the achievable quality in these parts. In this section, the main factors that affect the surface finish during AM, as well as the mathematical algorithms that can be used to estimate the surface quality from the selected process conditions, will be explained.

Among the distinct process parameters that can influence the surface finish in the AM methods, the layer thickness and surface orientation angle can be remarked on (Kumar and Saravana Kumar, 2015). There are different mathematical models that could be applied to predict the surface roughness depending on the AM technology and the process conditions that were assumed, as will be described below.

The surface finish of AM-generated parts can be represented in terms of the arithmetic roughness R_a . This roughness parameter can be deduced analytically from the geometrical relationship derived from the triangular contour that characterizes the surface irregularities of the parts processed by AM, according to the models that are described below.

The surface finish models remarked on in this section are limited to those based on a geometrical analysis that includes the positive and negative areas to both sides of the certain centerline to be defined along the part profile, due to their having a higher physical meaning and present a better accuracy. There are also some other algorithms that do not consider any profile centerline, although

they are more conservative and so provide an excessive value of surface roughness, and for this reason there were not contained in this chapter.

One of the most simplified models that can be used to estimate the arithmetic roughness consists of the following mathematical expression, which can be applied to the different free-form manufacturing techniques (Kumar and Saravana Kumar, 2015):

$$R_a = \frac{h}{4} \cos \theta \quad (16.29)$$

where h is the layer thickness and θ is the surface orientation angle.

For a better understanding, the schematic representation of Fig. 16.5 illustrates the relationship between the arithmetic roughness and geometrical parameters of AM processes such as the layer thickness and the surface orientation angle.

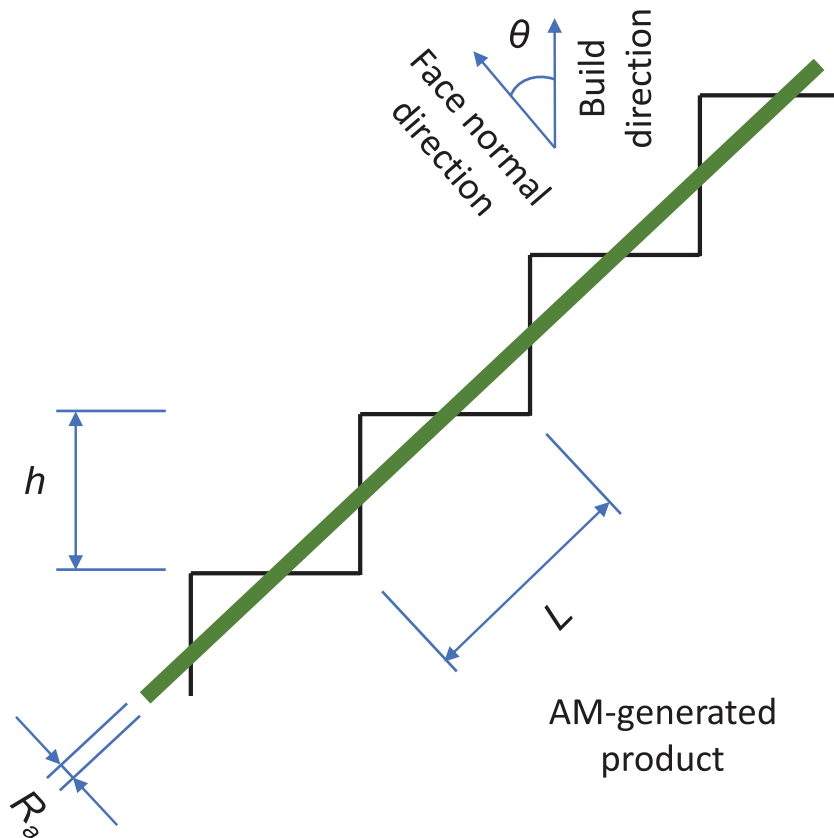


FIGURE 16.5

Schematic representation of surface roughness in additive manufacturing processes.

As described in the previous equation, if the layer thickness is increased a higher surface roughness will be obtained, which corresponds to the experimental observation of the parts produced by these manufacturing processes.

The evaluation length to be considered for calculating the surface roughness from the profile contour is also depicted in Fig. 16.5. This parameter is related to the layer thickness and surface orientation angle, as can be expressed in the following equation:

$$L = \frac{h}{\sin\theta} \quad (16.30)$$

The following model is more adequate for predicting the surface roughness in poly-jet processes, allowing the influence of the surface profile angle to be included (Kumar and Saravana Kumar, 2015). This model provides a better description of the contribution of the drops generated during these MJ technologies:

$$R_a = \frac{h}{4} \left| \frac{\sin(\theta + \phi)}{\sin\phi} \right| \quad (16.31)$$

where h is the layer thickness, θ is the surface orientation angle, and ϕ is the surface profile angle.

Another model that can be employed to predict the accepted surface roughness during poly-jet processes is based on the following mathematical expression (Kumar and Saravana Kumar, 2015):

$$R_a = \frac{h}{4} (\tan\phi \sin\theta + \cos\theta) + K \quad (16.32)$$

where K represents the layer composition effect. This model is only valid for angle values that would provide a positive result for the mathematical expression $\tan\phi \sin\theta + \cos\theta$.

The model developed by Ahn et al. (2012) allows the effect of the curved border of successive layers of the part surface that is originated in laminated object manufacturing (LOM) methods to be described. These authors distinguish among three different profile orientations such as up-facing surface, vertical surface, or down-facing surface, and provide specific algorithms for each of these processing conditions.

The mathematical expression of this model for up-facing surface, vertical surface, or down-facing surface will be:

$$R_a = \frac{1}{L} \sum_{i=1}^N \int_{x_i}^{x_{i+1}} f_i(x) dx \quad (16.33)$$

where L is the evaluation length for the surface profile, x_i and x_{i+1} are the characteristic points for each interval along the part profile, and $f_i(x)$ is the function that represents the deviation in each profile interval.

The function $f_i(x)$ will adopt a certain expression in each profile interval as a consequence of the vertical position of profile centerline x_L , the vertical position of profile peak x_P , and the layer thickness h . These mathematical expressions will differ in the case of up-facing surface, vertical surface, or down-facing surface.

The vertical position of profile centerline and profile peak that are contained in this model, can be calculated as follows:

$$y_L = \tan(\pi - \theta)(x - k) \quad (16.34)$$

$$y_P = ax^2 + d \quad (16.35)$$

where θ denotes the surface orientation angle, which must be comprised between zero and $\pi/2$, k is the distance from the origin along the x axis direction, which will be estimated from a specific position in the surface profile and a certain correction constant, a is the width of the parabolic function that represents the curved contour, which will depend on the properties of the laser and resin used during the LOM technique, and d is the penetration depth into the previous layer.

The round borders that can be originated on the part surface during the execution of FDM techniques can be studied by the model suggested by [Kaji and Barari \(2015\)](#). These authors employed the following algorithm to determine the surface finish in these free-form manufacturing processes:

$$R_a = \frac{1}{L} \sum_{i=1}^3 A_i \quad (16.36)$$

where L identifies the evaluation length for the surface profile, A_{ext1} and A_{ext2} are triangular areas of both extremities of each layer border, and A_0 is the round area of the central interval of deposited layer. If the value of these three areas is deduced through an easy calculation from the geometry of the profile contour, the arithmetic roughness of final surface can be predicted.

If the fluctuation in the size and position of the successive deposited layers are considered, the calculation of the surface finish becomes more complicated, and other more refined models should be applied. In this sense, [Lalehpour and Barari \(2018\)](#) proposed a model that serves to estimate the surface roughness that would be provoked by each layer regarding the average centerline to be derived from the least square fitting along the totality of the part contour.

According to the model developed by [Lalehpour and Barari \(2018\)](#), the arithmetic roughness can be estimated from the successive areas originated along the surface profile regarding the average centerline:

$$R_a = \sum_{i=1}^n \frac{A_i}{L_i} \quad (16.37)$$

where A_i and L_i are the summatory of areas and the profile length for the interval of the surface profile that correspond to each deposited layer, and can be calculated using the following expressions:

$$A_i = \frac{(x_i)^2 \sin(2\mu)}{4} + \frac{(t_{i+1} - t_i - x_i)P_i}{2} + \frac{(b_{i+1} - b_i - P_i)\sin(2\mu)}{4} \quad (16.38)$$

$$L_i = x_i \sin \mu + \frac{P_i}{\cos \mu} + (b_{i+1} - b_i - P_i) \cos \mu \quad (16.39)$$

where μ is the angle between the base and the average centerline, x_i is the cross point of the average centerline in each deposited layer, P_i is the position of the average centerline in the edge of each deposited layer, and (t_i, b_i) and (t_{i+1}, b_{i+1}) are the coordinates that correspond to the initial point of the current layer and the next layer, respectively.

The position of the average centerline in the edge of each deposited layer can be calculated from the main parameters of the layer geometry as follows:

$$P_i = \frac{t_{i+1} - h}{m} - b_i \quad (16.40)$$

where h represents the layer thickness and m is the slope of the average centerline.

Other mathematical models with distinct formulations that could be required to properly describe the influence of other factors involved in different free-form manufacturing processes can be also applied. In this sense, the following algorithm was developed by [Bikas et al. \(2016\)](#) to identify the surface quality associated with laser-based processes such as the SLA techniques:

$$R_a = D_p \ln \left[\sqrt{\frac{2}{\pi}} \frac{P_L}{W_0 V_S E_C} \frac{\sin \theta}{4 \tan \theta} \right] - \delta_0 \frac{\sin \theta}{4 \tan \theta} \quad (16.41)$$

where D_p denotes the depth of penetration on the product material, P_L is the power of the laser generator, W_0 is the diameter of the laser beam, V_S is the scanning speed of the laser, E_C is the critical exposure time, δ_0 is the overcure of the laser beam, and θ is the surface orientation angle.

Some AM techniques such as selective laser melting (SLM) can provoke the presence of adhered particles on the part surface. In this case this phenomenon must be considered during the process modeling in order to guarantee adequate prediction of the surface finish. The mathematical model proposed by [Strano et al. \(2013\)](#) can be assumed to estimate the surface integrity when this phenomenon occurs:

$$R_a = \iint |F(x, y) - \bar{F}| dx dy \quad (16.42)$$

where $F(x, y)$ is the height in the part surface at the point of coordinates (x, y) , and $\bar{F}$ is the average height in the total extension of the part surface under study.

The following expression can be adopted to attend to the distinct zones that appear in the surface contour:

$$R_a = \frac{1}{P} \int_0^{P_0} |F(x) - \bar{F}| dx + \frac{1-\lambda}{P} \int_{P_0}^P |F(x) - \bar{F}| dx + \frac{\lambda}{P} \int_{P_0}^P |F'(x) - \bar{F}| dx \quad (16.43)$$

where P is the distance between successive layers, $P - P_0$ is the length of the adhered particle in the profile direction, λ is the width of the adhered particle in the cross-section direction, $F(x)$ is the one-dimensional profile that describes the stair contour provoked by the successive layers, and $F'(x)$ is the one-dimensional profile that corresponds to the surface contour that includes the irregularities originated by the partially bonded particles, which can be determined by the following expression:

$$\bar{F} = \frac{1}{P} \int_0^{P_0} F(x) dx + \frac{1-\lambda}{P} \int_{P_0}^P F(x) dx + \frac{\lambda}{P} \int_{P_0}^P F'(x) dx \quad (16.44)$$

Ahn et al. (2009) employed a methodology that is based on registering a certain surface roughness database for different process conditions, provided that the surface roughness that would correspond to a certain value of surface profile angles could be deduced from the information comprised in the database when it is not possible to proceed to the measurement of this zone of the part surface. A simple expression like the following one can be used in this case to estimate the surface finish for these other process conditions:

$$R_a(\theta_i) = R_a(\theta_s) + \frac{R_a(\theta_t) - R_a(\theta_s)}{\theta_t - \theta_s} (\theta_i - \theta_s) \quad (16.45)$$

where θ_i denotes the surface profile angle under study, and θ_s and θ_t are the nearest values of the surface profile angle that are saved inside the surface roughness database before and after the current value θ_i , respectively.

16.4 Accuracy improvement in additive manufacturing by optimization or compensation techniques

In free-form manufacturing processes, the achievable quality of the final products can be enhanced if some specific methods oriented to error compensation or process optimization are properly applied.

The totality of equations contained in the previous sections of this chapter could help to identify the factors with a higher influence on the dimensional accuracy of parts generated by AM, and the recommendable values that should be adopted for the different process parameters. The correction of existing error sources and a better selection of the process conditions can be used for improving the dimensional accuracy of the AM-generated parts.

Several mathematical methods that can serve to enhance the dimensional and geometrical quality and surface integrity of the final parts through the compensation of error sources or the optimization of process parameters will be explained in this section.

16.4.1 Optimization of part orientation in additive manufacturing

The selection of an adequate part orientation can be convenient in order to improve the geometrical accuracy and surface quality of the products obtained by free-form manufacturing processes. For this reason, in this section some methods that can be employed for this purpose will be described.

Among the optimization or compensation methods that will be presented as follows, not only those oriented strictly to the enhancement of the part accuracy are included, but also to other aspects such as the minimization of material amount for the support structure and the minimization of the overall production time.

The model developed by Paul (2013) allows optimization of the dimensional accuracy of produced parts, as well as minimization of the volume of support structure. It consists of a multiobjective model that comprises a penalty-based optimization. The following expression represents the objective function $f(\beta_x, \beta_y)$ that can be considered to deduce the enhanced part orientation in the direction of x and y machine axes according to this mathematical model:

$$f(\beta_x, \beta_y) = \sum_{i=1}^{n_{cyl}} p_i \omega_i + \sum_{j=1}^{n_f} p_j \omega_j + \omega_s V_{s,nor} \quad (16.46)$$

where β_x and β_y are the rotation angles to be assumed around the x and y axes directions, respectively, p_i and p_j are penalties defined for cylindrical features and planar features, respectively, $V_{s,nor}$ is the normalized volume of the support structure, ω_i , ω_j , and ω_s are coefficients to be introduced in this model for the cylindrical features, planar features, and support structure, and the i and j subscripts are employed to represent the i -th cylindrical feature and j -th planar feature of the part to be manufactured.

The penalties p_i and p_j of this equation for cylindrical and planar features, respectively, can be calculated using the following expressions:

$$p_i = 1 - (c_z^2)_{cyl,i} \quad (16.47)$$

$$p_j = (c_z^2)_{fla,j} \quad (16.48)$$

where c_z is the component in the direction of z axis for the orientation vector that corresponds to the i -th cylindrical feature or j -th planar feature.

The volume of the support structure to be implemented in the model will be normalized according to the following equation:

$$V_{s,nor}(\beta_x, \beta_y) = \frac{V_s(\beta_x, \beta_y) - V_{s,min}}{V_{s,max} - V_{s,min}} \quad (16.49)$$

where V_s is the volume of the support structure for the part orientation defined by the rotation angles β_x and β_y around to the x and y axes directions, and $V_{s,\min}$ and $V_{s,\max}$ are the minimum and maximum values for the volume of the support structure.

The following expression can be employed to determine the required values for the coefficients ω_i , ω_j , and ω_s of the mathematical model:

$$\sum_{i=1}^{n_{\text{cyl}}} \omega_i + \sum_{j=1}^{n_{\text{pla}}} \omega_j + \omega_s = 1 \quad (16.50)$$

where the i and j subscripts will serve to identify the i -th cylindrical feature and j -th planar feature, respectively, of the CAD model.

Other methods that can be applied to improve the part orientation include the model presented by [Thrimurthulu et al. \(2004\)](#), which can serve to deduce the optimized surface roughness and build time by selecting the appropriate values of deposition orientation.

According to this model, an objective function f must be calculated using the following mathematical expression. The optimized part orientation can be determined through the process conditions of the free-form manufacturing process that provide the minimum value of the objective function:

$$f = \omega_1 R_a + \omega_2 T_e \quad (16.51)$$

where R_a is the surface roughness of the manufactured part, T_e is the build time that results from the process conditions, and ω_1 and ω_2 are the coefficients that must be selected to express the desired relevance for each of both factors of these equation to be optimized. These coefficients can adopt values between 0 and 1, and must satisfy the following condition:

$$\omega_1 + \omega_2 = 1 \quad (16.52)$$

In order to deduce the optimum part orientation, the following transformation matrix must be applied to the part design of the CAD model:

$$T_{\text{rot}} = \begin{bmatrix} n_x^2(1 - \cos\beta) + \cos\beta & n_x n_y(1 - \cos\beta) - n_z \sin\beta & n_x n_z(1 - \cos\beta) + n_y \sin\beta \\ n_x n_y(1 - \cos\beta) & n_y^2(1 - \cos\beta) + \cos\beta & n_y n_z(1 - \cos\beta) - \sin\beta \\ n_x n_z(1 - \cos\beta) & n_y n_z(1 - \cos\beta) + n_z \sin\beta & n_z^2(1 - \cos\beta) + \cos\beta \end{bmatrix} \quad (16.53)$$

where β is the rotation angle to be applied to the CAD model and (n_x, n_y, n_z) is the unitary vector that establishes the rotation axis.

The surface roughness for the different part orientations must be determined by measuring the part surface, while the build time can be deduced theoretically from the number of slices that will be required to generate the complete surface of the final product.

16.4.2 Compensation of extruder errors in additive manufacturing

The effect of the extruder errors on the dimensional accuracy of parts produced by free-form manufacturing technologies can be reduced by adopting a compensation method for these error sources.

Among the possible alternatives for this purpose, the mathematical model developed by Wang et al. (2017) can be applied. This model serves to correct not only the position errors that can be present on the extruder of AM machines, but also the shape deformations provoked by material phase change during these manufacturing processes.

According to these authors, the following expression can be utilized to deduce the function that would allow to compensate the original design by reducing the shape deviations originated by the extruder errors:

$$r^*(\gamma) = -r(\gamma) - \frac{r_0(\gamma)}{\beta_0 + \beta_{12}\sin(2\gamma) + \beta_{22}\cos(2\gamma)} \quad (16.54)$$

where $r_0(\gamma)$ is the theoretical location of the points of the part surface according to the CAD design, $r(\gamma)$ is the real location of surface points as a consequence of the position errors of extruder, and β_0 , β_{12} , and β_{22} are the coefficients reflected on the model of part deviations to represent the influence of the extruder errors. These coefficients will result from the second order term of this model, and can be determined from the irregularities registered on the part surface and the level of these error sources.

16.4.3 Compensation of shrinkage effect and beam offset

The geometrical accuracy of the mechanical parts obtained by AM techniques could be enhanced if a compensation method oriented to diminish the influence of material shrinkage is employed. There are distinct mathematical algorithms that can be adopted for this purpose, and an example of these algorithms will be shown in this section.

With the purpose of minimizing the dimensional deviations of the AM-generated parts, Mahesh (2004) proposed a shrinkage compensation method that consists of the definition of an appropriate scaling factor to be applied to the CAD model, as described in the following equation:

$$k = \frac{1}{1 + s} \quad (16.55)$$

where s is the value that corresponds to the material shrinkage originated on the manufactured part for the process conditions to be assumed. The scale factor k will be applied for the totality of geometrical features of the part to be produced by the free-form manufacturing process.

The deviations provoked by the beam offset can be also avoided by an adequate compensation criterion for beam configuration. Once the beam offset b has been properly estimated, its influence on the part accuracy can be minimized by the following criterion, which implies to assume within the CAD model a position corrector with a value equal to $b/2$ for the part contour along the x and y axes directions:

$$\Delta r^* = \frac{b}{2} \quad (16.56)$$

In the case of mechanical components of cylindrical geometry, the following mathematical expression suggested by Huang et al. (2015) can be adopted to determine the shrinkage compensation to be applied in the part radius:

$$r^*(\gamma) = - \frac{r_0^* + \alpha(r_0 + r_0^*)^a + \beta(r_0 + r_0^*)^b \cos(2\gamma)}{1 + a\alpha(r_0 + r_0^*)^{a-1} + b\beta(r_0 + r_0^*)^{b-1} \cos(2\gamma)} \quad (16.57)$$

where r_0^* is a global value of radial compensation for the entire part, r^* is the radial compensation to be considered for each value of position angle in the cross-section of the produced part, β is the angular position in the part contour during the additive manufacturing process, and a , b , α , and β are coefficients independent of the part radius that are contained in the material shrinkage prediction model.

16.5 Conclusions

Nowadays, companies need good knowledge about the main tools that integrate the new paradigm of Industry 4.0, also referred to as digital transformation or connected industry. Among the emergent technologies of Industry 4.0, additive manufacturing (AM) has great relevance for numerous sectors, and solid knowledge about the functionalities that can be guaranteed by these manufacturing processes in terms of dimensional accuracy are essential. In this chapter, the main factors related to the dimensional quality of the parts obtained by these free-form manufacturing techniques and the mathematical modeling that serves to represent the influence of the different process conditions on the part accuracy have been reviewed. The models that can be applied to predict the dimensional and geometrical accuracy or the surface roughness from the distinct process parameters of AM were explained. Among the factors considered in these algorithms, the layer thickness, surface orientation angle, surface profile angle, z-error, xy-error, beam offset, lamination borders, penetration depth, extruder errors, fused deposition borders, layer composition, particle adhesion, and other related factors are included. The mathematical algorithms shown in this book could be employed to deduce the configuration and parameters that must be adopted in order to enhance the performance of AM techniques and to obtain better dimensional accuracy in the produced parts.

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